

# *Empathy modulates the temporal structure of social attention*

Article

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1 Empathy Modulates the Temporal Structure of Social Attention

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*Author Contributions.*

30

31 *NH* carried out the statistical analysis and wrote the initial draft of the paper. *BC, EM, and*  
32 *AH* conceived of the study design, coordinated data collection and provided modifications to  
33 the initial manuscript draft. All authors declare that they have no conflicting or competing  
34 interests in relation to this article.

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## Abstract

Individuals with low empathy often show reduced attention towards social stimuli. A limitation of this literature is the lack of empirical work that has explicitly characterised how this relationship manifests itself over time. We investigate this issue by analysing data from two large eye-tracking datasets (total  $N = 176$ ). Via growth-curve analysis, we demonstrate that self-reported empathy (as measured by the empathy quotient - EQ) predicts the temporal evolution of gaze behavior under conditions where social and non-social stimuli compete for attention. In both datasets, we found that EQ not only predicted a global increase in social attention, but predicted a different temporal profile of social attention. Specifically, we detected a reliable effect of empathy on gaze towards social images after prolonged viewing. An analysis of switch latencies revealed that low EQ observers switched gaze away from an initially fixated social image more frequently and at earlier latencies than high EQ observers. Our analyses demonstrate that modeling these temporal components of gaze signals may reveal useful behavioral phenotypes. The explanatory power of this approach may provide enhanced biomarkers for conditions marked by deficits in empathy related processes.

*Keywords:* Eye-tracking; empathy, social attention

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67           To enable successful interactions with the environment, organisms must  
68 preferentially attend to socially significant stimuli. Failure to engage with conspecifics can  
69 result in exclusion and status loss, which are significant and recurrent fitness threats [1].  
70 Moreover, attending to social stimuli allows the accumulation of strategically beneficial  
71 information such as the physical strength of a potential rival, the social standing of a  
72 potential ally, or the genetic fitness of a potential mate [2]. In humans, such 'social attention'  
73 is also crucial for the development of communicative skills such as language acquisition and  
74 emotion recognition [3].

75           Empathy has been defined as the drive to identify with another person's emotions  
76 and thoughts, and to respond to these with an appropriate emotion [4]. In order to identify  
77 with another's emotions and respond appropriately, it is essential to attend to socially  
78 relevant cues such as bodily postures and facial expressions - which provide important  
79 information for decoding the emotional states of other people [5,6]. Social attention can  
80 therefore be conceptualised as an essential precursor to an empathic response. Support for  
81 this view has come primarily from case-control eye-tracking studies, which have  
82 demonstrated that individuals with deficits in some empathy related processes also show  
83 deficits in social attention. For instance, a recent meta-analysis revealed robust evidence  
84 that Autism Spectrum Conditions (ASC) are associated with a reduction in social attention  
85 that generalises across a wide range of tasks and stimulus conditions [7]. Influential case-  
86 control eye-tracking studies have indicated that individuals with ASC exhibit reduced  
87 attention to biological relative to non-biological motion patterns [8] and exhibit a preference  
88 to direct gaze towards geometric patterns when they compete with videos of social  
89 interactions [9]. However, other studies have called into question whether social attention  
90 differences are meaningfully related to the aetiology and maintenance of ASC [10,11]. The  
91 heterogeneity in reported outcomes is possibly due to the heterogeneous nature ASC and  
92 the small sample sizes resulting from the practical issues associated with case-control  
93 designs. In this context, it is surprising that there is almost no literature that has attempted to

94 model *individual*, rather than *group* variation in social attention in the neurotypical  
95 population. One recent study has demonstrated that trait empathy is associated with a gaze  
96 bias towards social rewards in the neurotypical population [12]. Although this observation  
97 indicates that social attention is generally reduced in individuals with low empathy, the  
98 *features* of gaze behavior underlying this reduction remain fundamentally unclear.

99         The output of a typical eye-tracking experiment is a continuous stream of spatial  
100 coordinates that define the location of an observer's gaze over time. To describe individual/  
101 group differences in social attention, this time series is typically collapsed into the total gaze  
102 duration towards areas of interest (AOI's) containing social and non-social stimuli [7]. Whilst  
103 total gaze duration is an intuitive and easily interpretable metric, it necessarily involves the  
104 removal of informative components of the data contained within the temporal domain. Such  
105 an approach may therefore fail in describing more subtle differences between individuals  
106 that describe the dynamic nature of social attention. Although some previous studies of  
107 social attention have considered the temporal origin of group differences via divergence  
108 analyses [13-15] none have provided or tested a quantitative model of the entire time series.  
109 To our knowledge, no existing study has provided an explicit model of the temporal structure  
110 of social attention and tested predictions about individual-level social gaze behavior over  
111 time.

112         The motivation for investigating individual differences in the temporal structure of  
113 social attention is not purely data driven. At the theoretical level, prioritised perception of  
114 socially relevant signals is one of the most important functions of the visual system. As such,  
115 there is a major explanatory burden associated with identifying the features of gaze behavior  
116 underlying individual variation in this phenomenon. Neurocognitive theories propose that  
117 social attention is mediated by neural circuits that transduce sensory information about  
118 conspecifics and translate that information into value signals that bias the spatial allocation  
119 of gaze over time [16]. In order to more fully appreciate what drives humans to attend to  
120 social aspects of the world, one must investigate the individual characteristics that influence  
121 this inherently dynamic process. By extension, this research effort may have the corollary of

122 informing explanatory models of disordered social attention. Moreover, influential models  
123 propose that attention involves at least two distinct components of initial 'orienting' to and  
124 subsequent 'maintaining' of engagement with stimuli [17]. In global eye-tracking metrics,  
125 these two processes are conflated - total gaze duration towards social stimuli could reflect  
126 some combination of both the orienting and maintaining mechanisms. Delineating these  
127 mechanisms requires explicitly modeling the temporal components of the gaze signal. In  
128 general, we may expect empathy to primarily influence gaze behavior some time after  
129 stimulus presentation because arriving at an empathic response may require sampling many  
130 relevant cues from a scene. We may need to attend to multiple subjects in the scene,  
131 determine their event roles, recognise their facial expressions/ bodily postures and integrate  
132 this information over time before an empathic response is triggered. This idea is consistent  
133 with the recent observation that although empathy is predictive of gaze bias towards social  
134 images after prolonged viewing, it does not predict the initial saccadic deviation towards  
135 social images in a 'global effect' paradigm [12].

136 In the context of the preceding discussion, there is a clear lack of empirical work that  
137 has attempted to model the temporal structure of social attention and its relationship with  
138 individual social trait characteristics such as empathy. In this study, our goals were to i)  
139 characterise the extent of gaze bias towards social stimuli in a large sample of observers ii)  
140 model the time course of this social bias iii) determine how empathy modulates the time  
141 course of the social bias. We report data from two large eye tracking datasets, with a  
142 combined total of 176 observers.

## 143 **Dataset 1**

### 144 **Method**

#### 145 **Participants**

146 Ninety nine participants (58 females, *M* age= 23, *SD* age = 5) were recruited from in  
147 and around the University of Reading. Ethical approval for the study was obtained from the  
148 Research Ethics Committee of the University of Reading (Ethics ID: 2012/070/BC) and all  
149 participants provided informed consent. All participants had normal or corrected to normal

150 vision. All participants except one female completed the Empathy Quotient (EQ) [16] a  
151 reliable, behaviorally validated measure of trait empathy. The mean EQ score was 44.21  
152 (SD = 11.27), and the scores ranged from 25-73. This distribution of scores closely  
153 resembles that previously observed in large-scale surveys of the neurotypical population  
154 (e.g. [19]:  $N = 190$ ,  $M = 44.5$ ,  $SD = 10.7$ ).

155

## 156 **Stimuli**

157 Forty pairs of social and nonsocial reward images were taken from the International  
158 Affective Picture System (18 pairs [20]) and downloaded from publicly available creative  
159 common licensed images databases such as Flickr (22 pairs). All images were the same as  
160 used in [10], in which social reward images included one or more humans (e.g. happy  
161 individuals) while nonsocial reward images included rewarding nonsocial content (e.g. food,  
162 scenery and money - see Supplementary Material S1). All stimuli in the experiment  
163 subtended 15.4 x 9.15 degrees of visual angle (DVA), and pairs were separated by 5.29  
164 DVA (Fig 1 b).

165 To reduce the influence of extraneous sensory and affective differences between  
166 image pairs, all stimulus pairs were matched as closely as possible in terms of low level  
167 properties (e.g. luminance, contrast, saliency) as well as perceived valence and arousal -  
168 see Supplementary Material S1. In addition, to further characterize the influence of low-level  
169 confounds, we presented two *stimulus types*. All image pairs were manipulated via randomly  
170 rearranging 10 x 10 pixel grids to create a set of '*scrambled*' images in addition to the *intact*  
171 images. The logic of this manipulation is that if simple low-level variability between image  
172 pairs drives a gaze bias towards social images, we would expect to find a social bias of  
173 similar magnitude for both the intact and scrambled stimulus types. By contrast, if social bias  
174 is genuinely driven by the semantic content of the images, we would expect social bias to be  
175 substantially reduced for scrambled stimuli.

## 176 **Procedure**

177 Observers were seated 50 cm in front of a Tobii T60 eye-tracker with an inbuilt 1280

178 x 1024 pixel resolution monitor (60hz refresh rate) and sampling rate of 60Hz (Figure 1a).  
179 Stimuli were presented using E-Prime 2.0 (Psychology Software Tools, PA, USA [21])  
180 Following a 5-point calibration, participants completed the freeviewing task: Observers were  
181 informed that they would be presented with pairs of images side by side for 3 seconds, and  
182 that they were free to look wherever they liked during this period. Figure 1b depicts the trial  
183 sequence: observers were presented with a fixation cross for 500 ms, followed by a pair of  
184 the social and nonsocial stimuli for 3000 ms. To maintain engagement with the task, the  
185 color of the fixation cross changed from black to blue on 10% of trials. The participant was  
186 asked to report these changes via button press as rapidly as possible. Observers completed  
187 80 trials in total (40 image pairs, 2 stimulus types).

## 188 **Results**

### 189 **Aggregated Social Bias**

190 Data reduction was performed via the 'eyetrackingR' package, implemented in the R  
191 programming language [22] The display coordinates occupied by the social and nonsocial  
192 images on each trial were defined as areas of interest (AOIs). We first analysed the data by  
193 aggregating across the time dimension. To this end, we reduced the raw gaze data for each  
194 participant into the proportion trial time that gaze was directed into the social AOI and  
195 nonsocial AOI. This data was submitted to a general linear model with AOI (social,  
196 nonsocial) and stimulus type (intact, scrambled) as fixed effects. Reported significance tests  
197 of model coefficients were conducted via likelihood ratio tests of nested models containing  
198 the coefficients versus those without them. There was a main effect of AOI, indicating gaze  
199 bias towards social images  $\chi^2(1) = 104.02, p < .001$ . Moreover, the predicted interaction  
200 between AOI and stimulus type was detected  $\chi^2(1) = 18.92, p < .001$  (Figure 1c). The bias  
201 for social images was larger in the intact condition ( $\beta = 0.12$ ) than scrambled condition ( $\beta =$   
202  $0.05$ ). Adding EQ to the model revealed a 3 way interaction between AOI, stimulus type and  
203 EQ  $\chi^2(1) = 5.90, p = .020$ . Higher EQ was associated with a larger social bias for intact  
204 stimuli than scrambled stimuli (Figure 1d).

205

206

**INSERT FIGURE 1 HERE**

207

208 **Time-course of Social Bias.**

209 Having analysed the aggregated data expressed as total gaze duration, we next

210 aimed to estimate a parsimonious model that described the time course of social bias across

211 participants. For each observer, we first removed trials for which gaze failed to record for

212 more than 60% of a trial (16% of the data). Next, we reduced each observer's gaze data into

213 the proportion of gaze within the social and non-social AOI in each 100ms time bin from the

214 start to end of the trial. We then removed data from the first 100 ms time bin, since it

215 contained 3 SDs less than the mean number valid samples captured within all time bins. No

216 association was detected between EQ and the number of remaining data points when this

217 cleaning strategy was applied  $r(96) = -.019, p = .851$ .

218 Figure 2a depicts the time course of gaze proportion into the social AOI for intact

219 stimuli. This gaze bias towards social images is not time invariant (Figure 2a), nor is its time

220 course well described by a linear function (Figure 2b). The global pattern is an initial bias

221 towards the social AOI that peaks within the first 500 ms, followed by a nonlinear decline

222 and a partial recovery towards the end of the trial. To model these nonlinear components of

223 the time course, we proceeded via forward selection and tested the performance of models

224 that included higher-order time regressors [23]. To protect against overfitting, we tested the

225 generalisation performance of each model, using standard leave one out (LOO) cross-

226 validation procedures (see Supplementary Material S2, S3). Once linear and quadratic time

227 regressors were added, the addition of higher order terms failed to reduce residuals or

228 improve LOO performance, suggesting that more complex models were prone to overfitting.

229 Therefore, a model with AOI and linear and quadratic time regressors as fixed effects (AIC =

230 -6365.5) was retained as our global model of the time-course of the social bias (Figure 2c).

231 **Effect of Empathy on Time Course of Social Bias**

232           Having modelled the time course of the social bias pooled across participants, we  
233 next attempted to model variation at the individual level. We first tested whether empathy  
234 modulates the time-course of the social bias by defining EQ as a predictor of proportion of  
235 gaze in the social AOI within each 100 ms time bin. An effect of EQ as a predictor of gaze  
236 into the social AOI was detected within 3 ‘clusters’ of contiguous time bins (Figure 2d, see  
237 Supplementary Material S4 for a rationale for defining clusters). These were located *i*) at  
238 100-900 ms *ii*) at 1500-1600 ms *iii*) at 1800- 2900 ms. Given the multiple tests associated  
239 with this analysis, our type 1 error rate may have reached unacceptable levels. Therefore, to  
240 protect against false positives, we performed a bootstrapped cluster-based permutation  
241 analysis (Supplementary Material S4) akin to that typically applied to electroencephalogram  
242 data [24]. After this correction was applied, there was no detectable effect in the second  
243 cluster ( $p = .316$ ), whereas the chances of obtaining the summed statistics observed in the  
244 first and last cluster under the null hypothesis were estimated to be at  $p = .003$  and  $p = .002$   
245 respectively.

246           With this temporal influence of empathy established, we next proceeded to test  
247 models that added EQ as a fixed effect to our initial global model of the time-course  
248 (Supplementary Material S5). We first specified a *reduced interactive model*, which  
249 constrained EQ to interact only with AOI but not the time regressors. This led to improved  
250 model fit  $\chi^2(2) = 337.47$ ,  $p < .001$ , consistent with the previously observed generalised  
251 increase in social bias associated with high EQ . Next we specified a *fully interactive model*,  
252 which removed this constraint and allowed EQ to additionally interact with the time  
253 regressors. This further improved on the reduced interactive model  $\chi^2(4) = 72.70$ ,  $p < .001$ .  
254 To aid interpretation of this model, its predictions are plotted with the empirical data for 5  
255 observers (Figure 2e), whose EQ is ordered from left to right (low to high). The model  
256 predicts that EQ is associated with a generalised increase in gaze bias towards the social  
257 AOI (i.e. the vertical offset between the blue and green lines), but that this effect is  
258 particularly pronounced at the start and end of the trial. Given the complexity of this fully

259 interactive model, we again protected against overfitting via another LOO analysis, which  
260 confirmed that this model had the superior performance (Supplementary Material S5).

261 In good agreement with the results of our cluster-based analysis, this confirms that  
262 EQ is not only associated with a generalised increase in social bias, but also with a different  
263 temporal profile of social bias. Inspection of figure 2e reveals that EQ predicts an initial  
264 increase in social attention, but also a more sustained component that maintains social  
265 attention at the later portions of the trial.

266

267

***INSERT FIGURE 2 HERE***

268

269 One plausible mechanism for this sustained component is that, after being initially  
270 fixated, social images hold attention for longer durations in high empathy individuals than  
271 low empathy individuals. To test this possibility, we split trials according to the AOI that was  
272 initially fixated and analysed the latency at which observers switched their gaze to the  
273 alternate AOI. We reasoned that if empathy was associated with sustained attention on  
274 social images, this would be manifested in an interactive effect of EQ and initial AOI on gaze  
275 switch latency. Figure 3a depicts the proportion of observers who switched AOI as a  
276 function of the initial AOI, EQ (median split for visualisation) and time. Inspection of this  
277 figure reveals that low EQ individuals switched from the social AOI more frequently and at  
278 earlier latencies than high EQ individuals. The predicted interaction between EQ and initial  
279 AOI on switch latency was detected  $\chi^2(1) = 4.56, p = .030$ . Higher EQ was associated with  
280 later switching from the social AOI relative to the nonsocial AOI (Figure 3b).

281

282

***INSERT FIGURE 3 HERE***

283

284

**Dataset 2**

285 Our analyses of the first dataset indicate a robust effect of empathy on the time  
286 course of social attention. To further validate our initial findings, we next tested their  
287 generalisation performance via a re-analysis of an existing, independent dataset [12].  
288

## 289 **Method**

### 290 **Participants**

291 77 participants (42 females;  $M = 21$  years,  $SD = 3$  years) drawn from in and around  
292 the University of Reading campus completed the FV task. All participants had normal or  
293 corrected to normal vision. 68 (38 female) participants completed the online EQ  
294 questionnaire. The study was approved by the University of Reading Research Ethics  
295 Committee (Ethics ID: 2010/86/BC).

### 296 **Stimuli**

297 The images and image pairings were the same as those described for Dataset 1.

### 298 **Procedure**

299 The only procedural differences from those described in Dataset 1 were as follows.  
300 Participants were seated at 100 cm from a 1600 x 1200 pixel resolution colour monitor (75hz  
301 refresh rate). Eye movements were recorded via a video based eye-tracker with a sampling  
302 rate of 500hz (Eyelink 2, SR research). Stimuli were presented via Experiment Builder  
303 software [25]. The presentation duration of stimuli in this task was 5000 ms and stimuli  
304 subtended 5.59 x 4.19 DVA.

## 305 **Results**

### 306 **Aggregated Social Bias**

307 Inspection of Figure 4 reveals a pattern of results that very closely mirror those  
308 obtained from Dataset 1. There was again the same main effect of AOI  $\chi^2(1) = 91.40$ ,  $p$   
309  $<.001$  and interaction between AOI and stimulus type  $\chi^2(1) = 28.61$ ,  $p <.001$  (Figure 4a).  
310 The bias for social images was similarly larger in the intact condition ( $\beta = 0.13$ ) than  
311 scrambled condition ( $\beta = 0.04$ ). Adding EQ to the model revealed the same 3 way

312 interaction between AOI, stimulus type and EQ  $\chi^2 (1) = 18.21, p < .001$ . Higher EQ was  
313 associated with a larger social bias for intact stimuli, but not scrambled stimuli (Figure 4b).

#### 314 **Time-course of Social Bias**

315 We used the same data reduction strategy as reported for Dataset 1. We removed  
316 2.85% trials due to trackloss and again removed data from the first 100 ms timebin. No  
317 association was detected between EQ and the number of remaining data points when this  
318 cleaning strategy was applied  $r (67) = -.003, p = .981$ . The forward selection strategy  
319 revealed that a model involving AOI and a linear and quadratic time regressors as fixed  
320 effects (Figure 4c) again provided the best fit to the data (AIC -9639.3) and had the best  
321 generalisation performance (see supplementary material S6).

#### 322 **Effect of Empathy**

323 An effect of EQ as a predictor of social bias was detected within a cluster from 2800 -  
324 5000ms (*corrected*  $p = .009$  - Figure 4d). We again tested models that added EQ as a fixed  
325 effect to our initial model of the global data. The reduced interactive model again improved  
326 model fit  $\chi^2 (2) = 335.98, p < .001$ . Moreover, a fully interactive model further improved on the  
327 reduced interactive model  $\chi^2 (4) = 85.14, p < .001$ . EQ was primarily predictive of social bias  
328 towards the end of the trial (Figure 4d).

329 An analysis of switch latencies did not detect an interaction between initial AOI and  
330 EQ  $\chi^2 (1) = 3.52, p = .060$ , but the effect was similar in magnitude and direction to that  
331 observed in Dataset 1. Higher EQ was again associated with later switching from the social  
332 AOI relative to from the nonsocial AOI (Figure 4e, Figure 4f).

333

334

**INSERT FIGURE 4 HERE**

335

336

#### **Discussion**

337

338

In this study our major novel contributions were as follows: We i) provide an explicit  
model of the time course of social attention, ii) determine how the parameters of this model

339 are modulated by social trait characteristics of the observer iii) test this model by making  
340 quantitative predictions about the allocation of an individual's gaze over time. Across two  
341 large datasets, we found a number of similar findings. i) Observers exhibit a robust gaze  
342 bias towards social images ii) EQ is reliably associated with an increase in this bias iii) This  
343 effect of EQ is not time invariant - a model that allowed empathy to interact with the temporal  
344 components of the gaze bias provided a superior fit to a model that assumed a time-  
345 invariant effect of empathy. Specifically, empathy was found to reliably maintain gaze bias  
346 towards social images after prolonged viewing. iv) Higher EQ was associated with less  
347 frequent, and later switching from an initially fixated social image.

348         At the most fundamental level, our finding that gaze behavior is predicted by the  
349 social trait characteristics of the observer emphasises that the mechanisms underlying social  
350 attention are deeply enmeshed with other aspects of social cognition. The dynamic influence  
351 of empathy on gaze behavior suggests that empathy is not a passive affective resonance  
352 with the emotions of others and that wider contextual influences play feed-forward roles in  
353 how emotions are perceived and experienced. This fits with neurocognitive theories of  
354 empathy, which propose that empathy is implemented by a network of recursively connected  
355 cortical and subcortical sites [26]. It also fits well with multi-stage models of empathy, which  
356 propose that prolonged attention to social stimuli reflects a form of evidence gathering so  
357 that appropriate empathic responses can be generated [27,28].

358         Our findings appear consistent with recent pharmacological work, which indicates  
359 that administration of oxytocin (associated with the experience of empathy in humans and  
360 mesolimbic dopaminergic activity involved in responding to rewards) predicts maintained  
361 periods of eye-contact in Macaque monkeys [14]. We speculate the similarity of these  
362 findings with our own reflect some common mechanism that promotes prolonged perceptual  
363 selection of socially relevant inputs. Computational models of alternative forced choice  
364 behavior have been proposed that explicitly relate gaze behavior to value coding. The 'gaze  
365 cascade model' proposes that gaze and value coding mutually interact, resulting in an  
366 increased gaze towards preferred stimuli over time [29]. A consistent observation from both

367 of our datasets is that trait empathy is better able to predict gaze toward social rewards  
368 towards the end of the trial. One potential interpretation of this observation is that trait  
369 empathy is related to enhanced motivational salience of social stimuli. By extension, we  
370 speculate that the individual differences in the temporal evolution of eye-movement behavior  
371 observed in our study reflects some online behavioral correlate of the value-coding process.  
372 This inference relies on electrophysiological studies that show value-coding is a dynamic  
373 process, and requires accumulation of evidence over time [30]. This interpretation of  
374 empathy being related to the value coding of social rewards is also consistent with the  
375 observation that higher empathy is associated with greater reward-related striatal activation  
376 in response to socially stimuli [30]. Our free-viewing task, of course, did not require  
377 observers to make an explicit choice between two stimuli. Recent computational modeling of  
378 binary choice behavior indicates that impressive predictions of choice behavior can be  
379 generated by models that incorporate gaze behavior and the reward value of competing  
380 stimuli [32]. In this context, an interesting question concerns whether empathy similarly  
381 predicts different trajectories of social attention and different gaze cascade effects in choice-  
382 based paradigms.

383         In interpreting our findings, it is important to acknowledge that gaze behavior in  
384 response to complex rewarding scenes is likely to reflect the output of many dissociable and  
385 fundamental processes. As such, the pattern of results we found could also be driven by  
386 some combination of component processes found to vary as a function of empathy. This  
387 may include individual differences in gaze perception [33] expression recognition [34]  
388 temporal integration [15] and a precedence of local over global processing [35]. Our data  
389 cannot clarify the relative contribution of these factors. Moreover, gaze behavior is strongly  
390 determined by low-level properties, such as luminance contrast and spatial frequency profile.  
391 Although we attempted to protect against these issues with our matching procedures and  
392 use of scrambled control stimuli, our stimuli are still not immune to these issues. However,  
393 no study involving complex, naturalistic visual stimuli is completely resistant to these  
394 potential confounds.

395 In the absence of longitudinal data, a claim about the directionality of the causal  
396 relationship between empathy and social attention observed here is clearly over-reaching.  
397 Based on the available developmental literature, however, there are sensible grounds for  
398 proposing that some aspects of social attention precede empathy. Newborns exhibit robust  
399 orienting responses to conspecific stimuli (particularly faces) [36], whereas the cognitive  
400 components of empathy (such as theory of mind) emerge several years in development [37].  
401 In this context, our study could motivate well-controlled developmental studies that track the  
402 temporal structure of social attention across development and its shared trajectory with the  
403 development of empathic abilities.

404 Our findings have several important implications for the design of future studies. We  
405 observed that empathy can take effect on behavior several seconds after stimulus onset.  
406 Spontaneous mimicry, related to certain components of empathy [38] can also take effect  
407 several seconds after stimuli onset (e.g. in response to reward [39]). Findings like these may  
408 question the sensitivity of methods that rely on much briefer stimulus exposures, such as  
409 visual probe paradigms [40-42] in detecting differences between groups that vary in  
410 empathic traits. There is widespread enthusiasm for the idea that electrophysiological  
411 methods with high temporal resolution may further clarify the temporal brain dynamics of  
412 empathy [43,44] and distinguish between competing explanatory models. Based on the  
413 findings reported in this paper, we are additionally enthusiastic about the prospect of  
414 paradigms that employ concurrent recording of both EEG and gaze data. Capitalising on the  
415 high temporal resolution shared by these methods may lead to theoretical advancement by  
416 providing insight into the time-course of the neural signatures underlying empathy and their  
417 behavioral correlates. Motivated accounts of empathy suggest that observers may  
418 dynamically increase or decrease attention to social cues to regulate their emotional  
419 responses [28]. Paradigms that concurrently monitor gaze allocation and autonomic arousal  
420 over time could explicitly test the predictions of such models.

421           In general, our data demonstrate that considering the temporal structure of gaze  
422 signals may provide impetus towards enhanced behavioral phenotypes for conditions  
423 marked by deficits in one or more empathy related processes (ASC, Psychopathy, Bipolar  
424 Disorder, Schizophrenia [45-47]). More broadly, follow up experimentation of this variety can  
425 also help us answer the more fundamental question: What features of gaze behavior  
426 differentiate between individuals with and without these conditions? Failing to capitalize on  
427 the high-dimensional, time-varying nature of gaze signals necessarily entails restricting the  
428 information available for answering this question.

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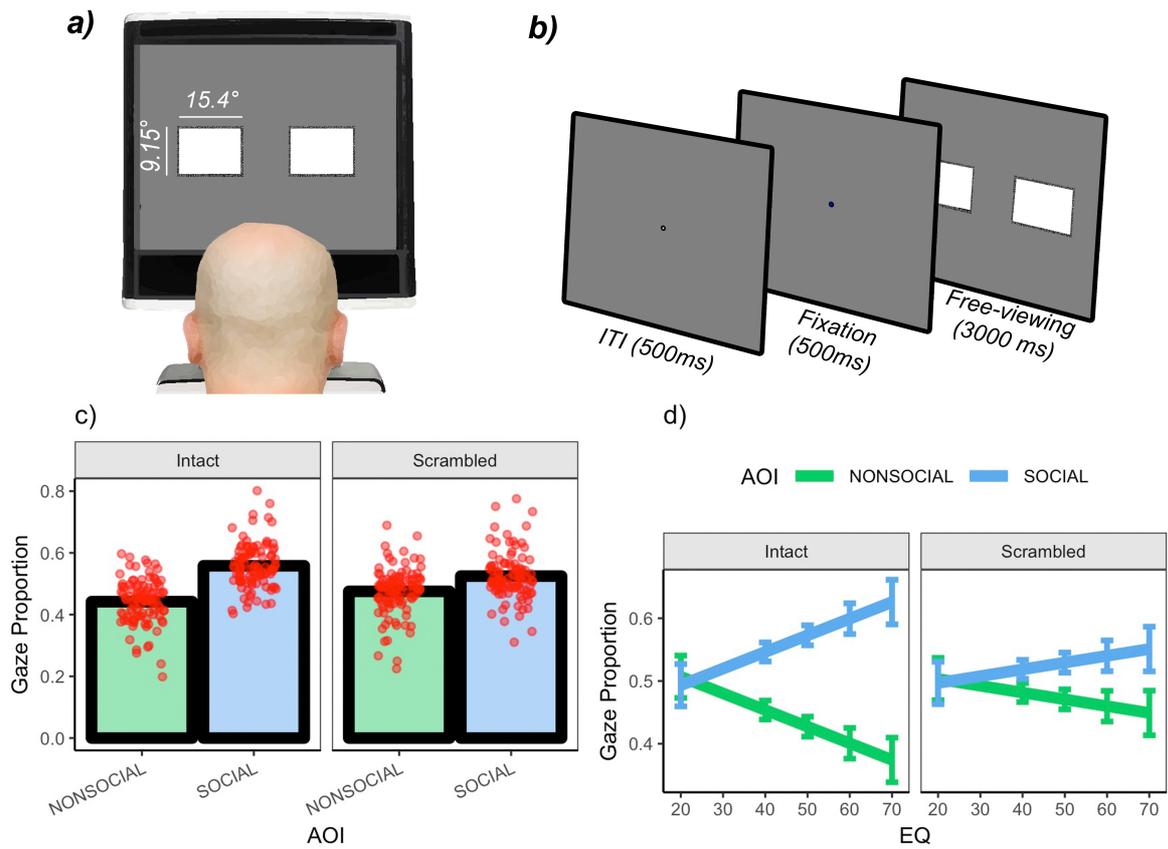
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### Figures



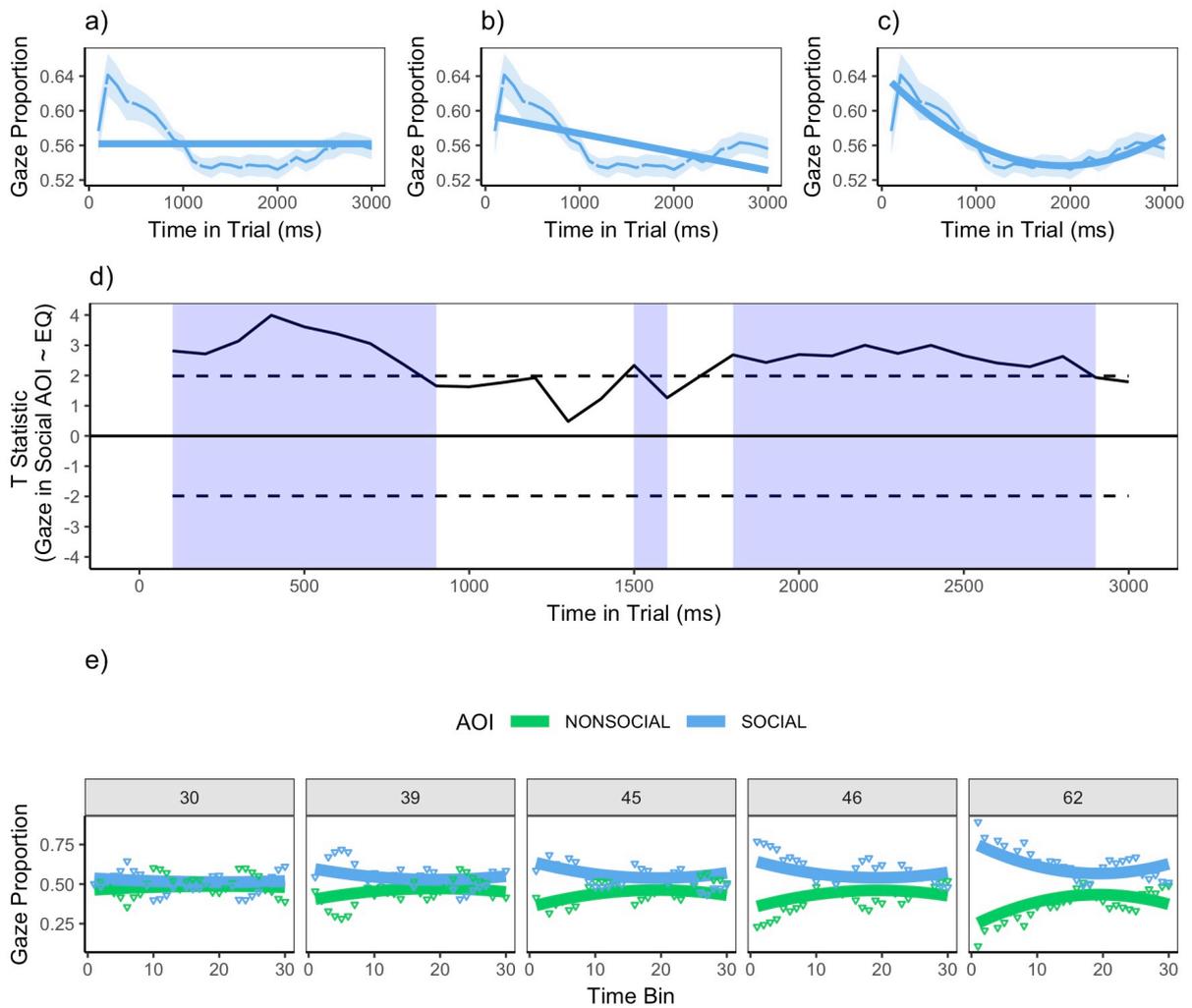
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554 *Figure 1. a) Schematic of experimental setup and b) trial sequence. c) Gaze proportion as a*

555 *function of AOI and stimulus type. Red points indicate individual data. d) Gaze proportion as*

556 *a function of AOI, stimulus type and EQ. Error bars are  $\pm 1$  SEM.*

557



558

559 *Figure 2.* a) Shows the time series fit to the gaze proportion into the social AOI with only AOI

560 as a fixed effect (no effect of time). b) Shows a fit to the same data with AOI and a linear

561 time regressor as fixed effects. c) Shows the the data fit with AOI and linear and quadratic

562 time regressors. d) Shows *t* statistics for the test that EQ is a linear predictor of gaze

563 proportion into the social AOI within each 100ms time bin. Shaded areas demarcate the time

564 bins wherein the statistic reaches the (uncorrected) threshold for rejecting the null

565 hypothesis. e) Shows predictions of the fully interactive model for 5 observers. The panel

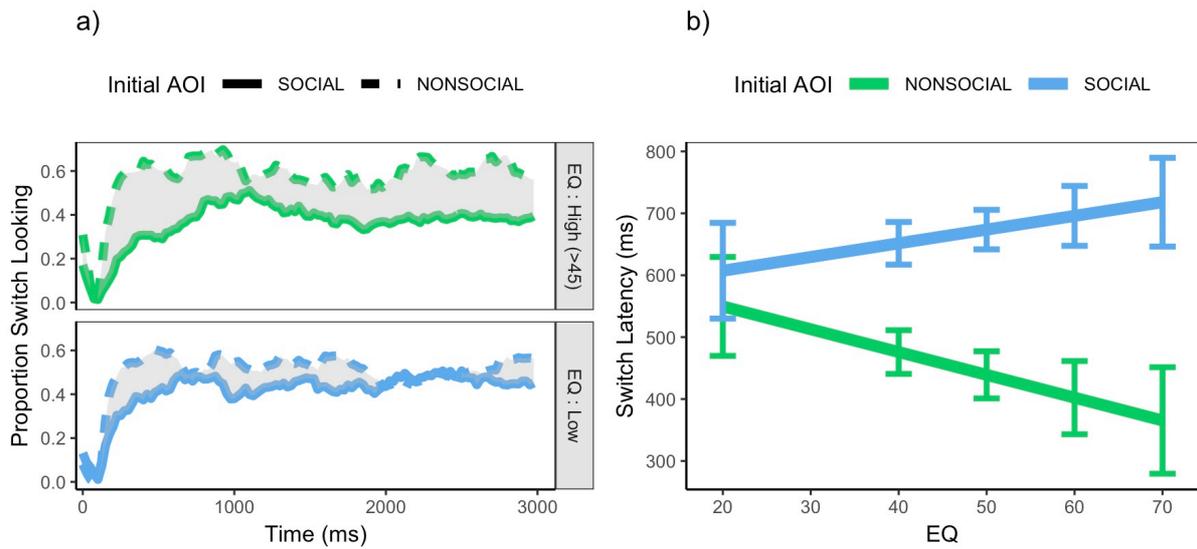
566 headers indicate the observer's EQ score. Solid lines are model predictions, points are the

567 empirical data.

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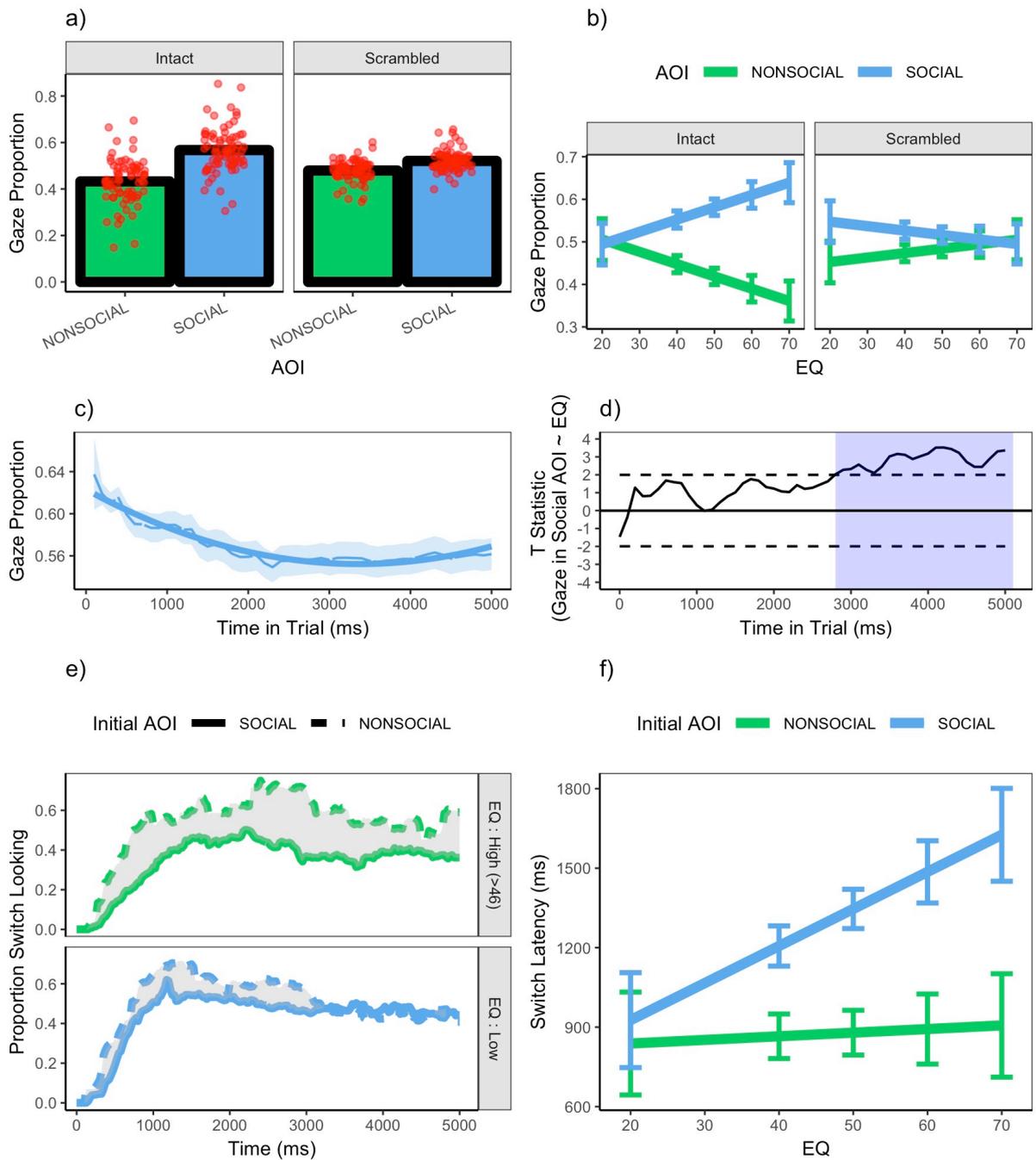


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573 *Figure 3.* a) Shows proportion of observers who switched to the alternate AOI as a function  
 574 of initial AOI, EQ (median split) and time b) Shows switch latency as a function of initial AOI  
 575 and EQ. Error bars are +/- 1 SEM.

576



578

579 *Figure 4.* a) Gaze proportion as a function of AOI and stimulus type. Red points indicate  
 580 individual data. b) Gaze proportion as a function of AOI, stimulus type and EQ. Error bars  
 581 are +/- 1 SEM. c) Shows the fit to gaze proportion time series with AOI and a linear and  
 582 quadratic time regressors as fixed effects. Data is shown for the social AOI. d) Shows *t*  
 583 statistics for the test that EQ is a linear predictor of gaze proportion into the social AOI within  
 584 each 100ms time bin. Shaded areas demarcate the time bins wherein the statistic reaches

585 the (uncorrected) threshold for rejecting the null hypothesis. e) Shows proportion of  
586 observers who switched to the alternate AOI as a function of initial AOI and EQ (median  
587 split) f) Shows switch latency as a function of initial AOI and EQ. Error bars are +/- 1 SEM.

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