Empathy modulates the temporal structure of social attention

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29   *Author Contributions.*

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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.

35

36   Abstract

37   Individuals with low empathy often show reduced attention towards social stimuli. A limitation

38   of this literature is the lack of empirical work that has explicitly characterised how this

39   relationship manifests itself over time. We investigate this issue by analysing data from two

40   large eye-tracking datasets (total N = 176). Via growth-curve analysis, we demonstrate that

41   self-reported empathy (as measured by the empathy quotient - EQ) predicts the temporal

42   evolution of gaze behavior under conditions where social and non-social stimuli compete for

43   attention. In both datasets, we found that EQ not only predicted a global increase in social

44   attention, but predicted a different temporal profile of social attention. Specifically, we

45   detected a reliable effect of empathy on gaze towards social images after prolonged viewing.

46   An analysis of switch latencies revealed that low EQ observers switched gaze away from an

47   initially fixated social image more frequently and at earlier latencies than high EQ observers.

48   Our analyses demonstrate that modeling these temporal components of gaze signals may

49   reveal useful behavioral phenotypes. The explanatory power of this approach may provide

50   enhanced biomarkers for conditions marked by deficits in empathy related processes.

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

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

Empathy has been defined as the drive to identify with another person's emotions and thoughts, and to respond to these with an appropriate emotion [4]. In order to identify with another's emotions and respond appropriately, it is essential to attend to socially relevant cues such as bodily postures and facial expressions - which provide important information for decoding the emotional states of other people [5,6]. Social attention can therefore be conceptualised as an essential precursor to an empathic response. Support for this view has come primarily from case-control eye-tracking studies, which have demonstrated that individuals with deficits in some empathy related processes also show deficits in social attention. For instance, a recent meta-analysis revealed robust evidence that Autism Spectrum Conditions (ASC) are associated with a reduction in social attention that generalises across a wide range of tasks and stimulus conditions [7]. Influential case-control eye-tracking studies have indicated that individuals with ASC exhibit reduced attention to biological relative to non-biological motion patterns [8] and exhibit a preference to direct gaze towards geometric patterns when they compete with videos of social interactions [9]. However, other studies have called into question whether social attention differences are meaningfully related to the aetiology and maintenance of ASC [10,11]. The heterogeneity in reported outcomes is possibly due to the heterogeneous nature ASC and the small sample sizes resulting from the practical issues associated with case-control 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 χ^2 (1) = 104.02, p <.001. Moreover, the predicted interaction

200   between AOI and stimulus type was detected χ^2 (1) = 18.92, p <.001 (Figure 1c). The bias

201   for social images was larger in the intact condition (β = 0.12) than scrambled condition (β =

202   0.05). Adding EQ to the model revealed a 3 way interaction between AOI, stimulus type and

203   EQ χ^2 (1) = 5.90, p =.020. Higher EQ was associated with a larger social bias for intact

204   stimuli than scrambled stimuli (Figure 1d).

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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 (Figue 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 χ^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 χ^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 χ^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 χ^2 (1) = 91.40, p

309   <.001 and interaction between AOI and stimulus type χ^2 (1) = 28.61, p <.001 (Figure 4a).

310   The bias for social images was similarly larger in the intact condition (β = 0.13) than

311   scrambled condition (β = 0.04). Adding EQ to the model revealed the same 3 way

13

312   interaction between AOI, stimulus type and EQ χ^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 χ^2 (2) = 335.98, *p* <.001. Moreover, a fully interactive model further improved on the

327   reduced interactive model χ^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 χ^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   In this study our major novel contributions were as follows: We i) provide an explicit

338   model of the time course of social attention, ii) determine how the parameters of this model

14

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

15

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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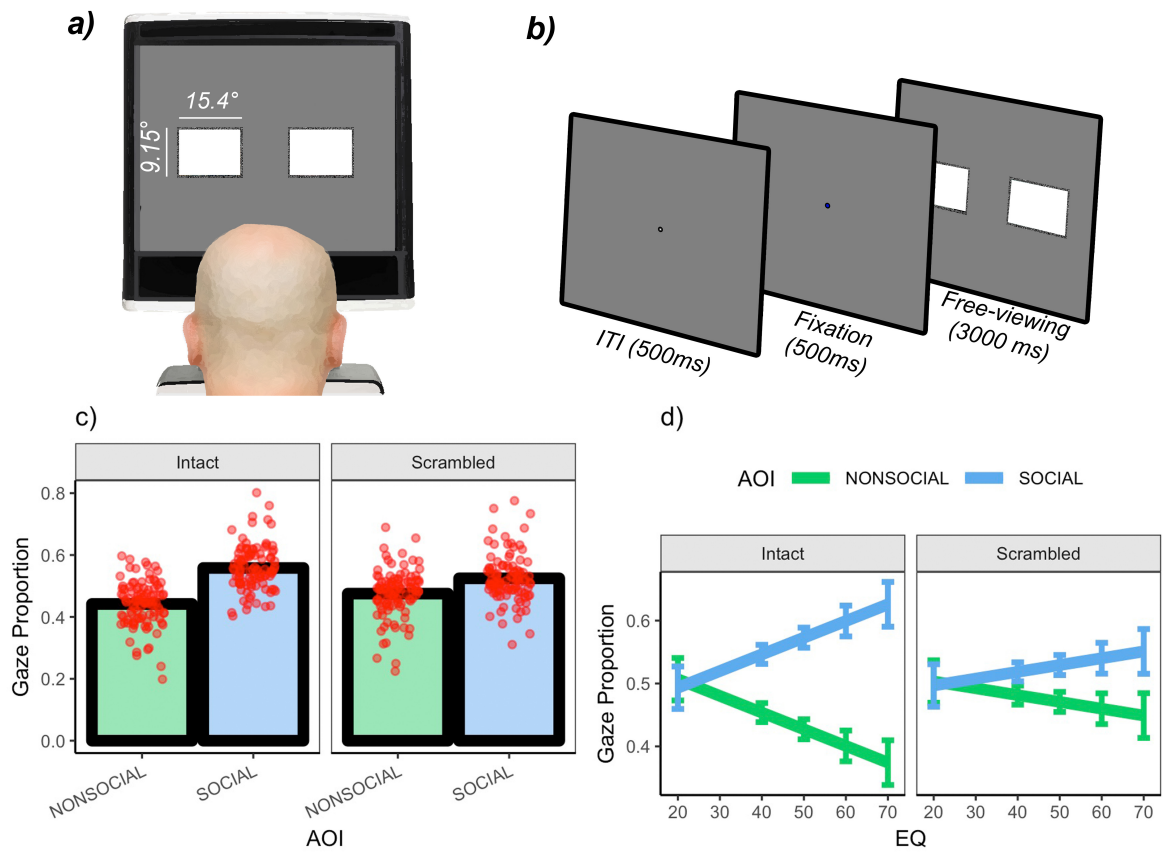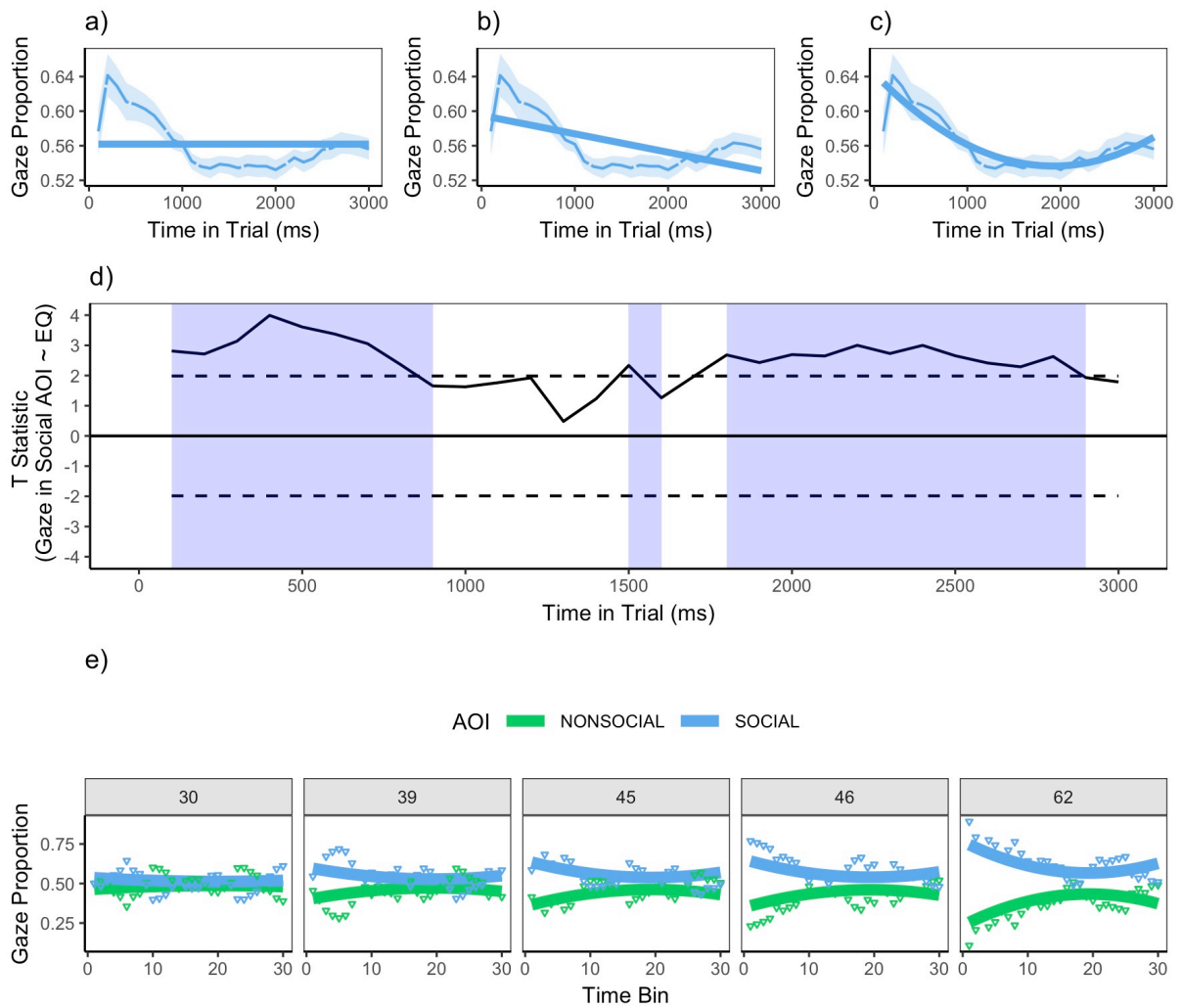548   Neurosci. 2009 Winter;21(1):59–67.

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Figures

Figure 1. a) Schematic of experimental setup and *b)* trial sequence. c) Gaze proportion as a function of AOI and stimulus type. Red points indicate individual data. *d)* Gaze proportion as a function of AOI, stimulus type and EQ. Error bars are +/- 1 SEM.

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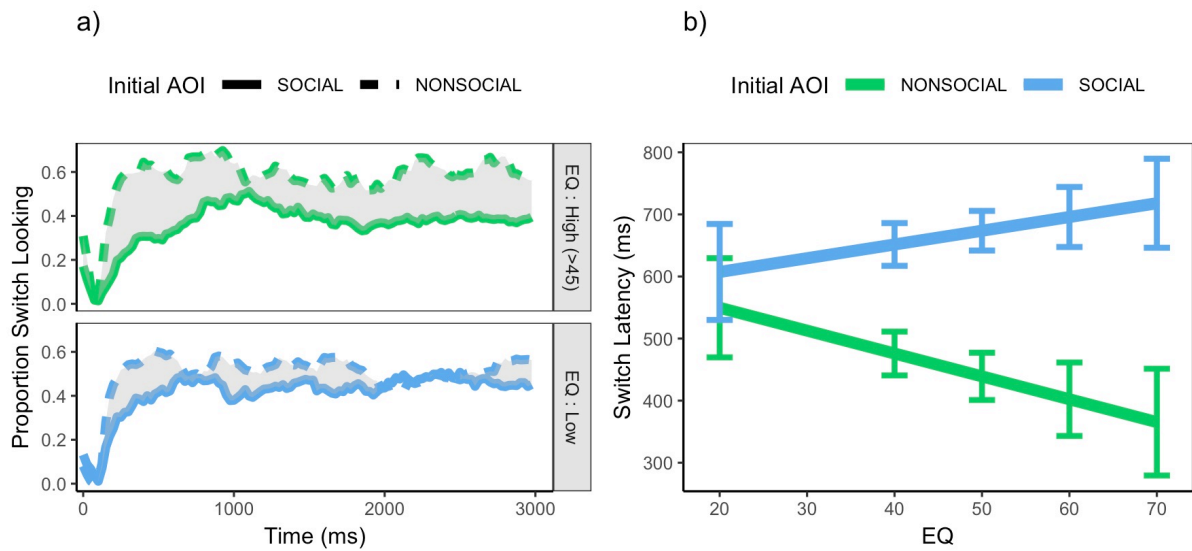
566   headers indicate the observer's EQ score. Solid lines are model predictions, points are the
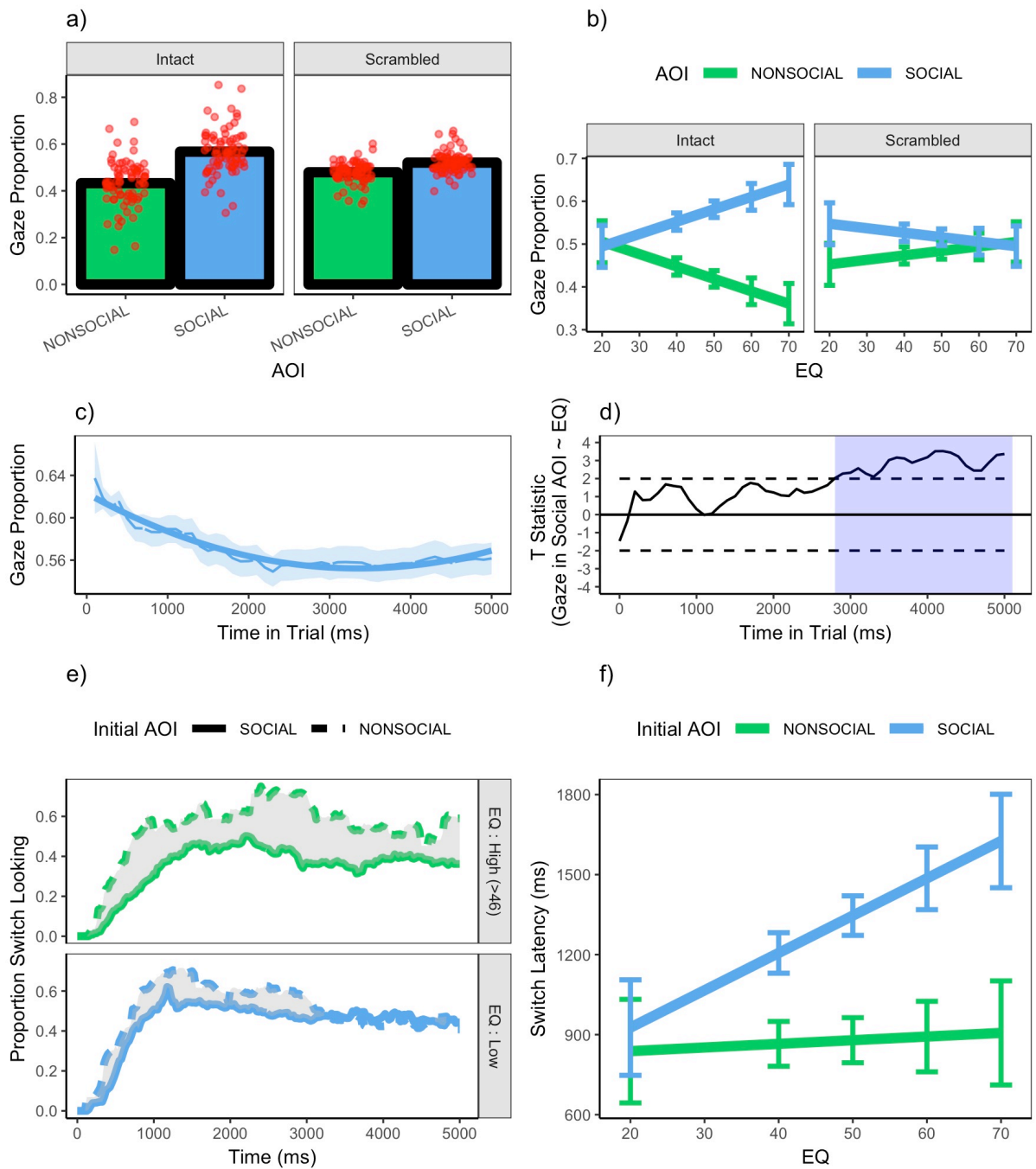
567   empirical data.

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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

Figure 4. a) Gaze proportion as a function of AOI and stimulus type. Red points indicate

individual data. b) Gaze proportion as a function of AOI, stimulus type and EQ. Error bars

are +/- 1 SEM. c) Shows the fit to gaze proportion time series with AOI and a linear and

quadratic time regressors as fixed effects. Data is shown for the social AOI. d) Shows *t*

statistics for the test that EQ is a linear predictor of gaze proportion into the social AOI within

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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