1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

Title

Neural decoding of competitive decision-making in Rock-Paper-Scissors

Authors

Denise Moerel[1], Tijl Grootswagers[1,2], Jessica L. L. Chin[1], Francesca Ciardo[3], Patti Nijhuis[1,4] Genevieve L. Quek[1], Sophie Smit[1] & Manuel Varlet[1,5]

Affiliations

[1] The MARCS Institute for Brain, Behaviour and Development, Western Sydney University, Australia
[2] School of Computer, Data and Mathematical Sciences, Western Sydney University, Australia
[3] Department of Psychology, University of Milan-Bicocca, Milan, Italy
[4] Department of Music, Arts and Culture Studies, University of Jyväskylä, Finland
[5] School of Psychology, Western Sydney University, Australia

Corresponding author email
d.moerel@westernsydney.edu.au

Keywords
EEG; Hyperscanning; Decision-making; Decoding; Competition

Word count
5160

ABSTRACT

Social interactions are fundamental to daily life, yet social neuroscience research has often studied individuals' brains in isolation. Hyperscanning, the simultaneous recording of neural data from multiple participants, enables real-time investigation of social processes by examining multiple brains while they interact. Previous hyperscanning research has largely focused on cooperative tasks, with fewer studies examining competitive contexts. Here, we obtained electroencephalography (EEG) hyperscanning data from 62 participants (31 pairs) who played a computerised version of the Rock-Paper-Scissors game, a classic paradigm for studying competitive decision-making. Although the optimal strategy is to be unpredictable and thus act randomly, participants exhibited behavioural biases, deviating from this ideal. Using multivariate decoding methods to measure neural representations within the two players' brains in interaction, we found information about decisions made by participants during gameplay, revealing certain strategies. Notably, losers uniquely represented information about prior trials, suggesting this may impair optimal performance. These results reveal how competitive decision-making is shaped by cognitive biases and previous outcomes, highlighting the difficulty of achieving randomness in strategic contexts. This work advances our understanding of decision-making and cognitive dynamics in competitive interactions.

1. INTRODUCTION

Social interactions form a crucial part of our daily lives. Although studies in the field of social neuroscience have predominantly focused on individual participants during passive tasks, for example observing facial expressions and interactive behaviours (Krumhuber et al., 2023; McMahon & Isik, 2023), there has been a recent shift towards multi-brain or hyperscanning methods as they allow for the study of neural processes underlying real-time social interactions (Lehmann et al., 2023; Redcay & Schilbach, 2019). In this approach, neural data are recorded simultaneously from two or more participants interacting in real-time, enabling investigations of how brains dynamically respond and coordinate with one another (Czeszumski et al., 2020; Dumas et al., 2010; Zamm et al., 2024). Previous hyperscanning work has advanced our understanding of human cooperative activities in which brains constantly need to monitor and predict one's own and others' actions (Cheng et al., 2024; Dumas et al., 2010; Keller et al., 2014; Moreau et al., 2024; Tognoli et al., 2007; Varlet et al., 2020; Zamm et al., 2024). However, less research has investigated competitive activities (Babiloni et al., 2007; Balconi & Vanutelli, 2017; Cui et al., 2012; Nam et al., 2020; Sinha et al., 2016). Importantly, whereas cooperation requires behavioural predictability to facilitate the anticipation of each other's actions and intentions, competition often requires behavioural unpredictability to gain an advantage (Glover & Dixon, 2017; Vesper et al., 2011). The current study investigates the neural processes underpinning decision performance in competitive activities.

Previous hyperscanning research has primarily focused on interbrain synchrony – the alignment of neural activity between interacting individuals – which has been shown to scale up with the level of

62 cooperation (Fallani et al., 2010; Hu et al., 2018; Toppi et al., 2016). A few studies that directly

63 compared interbrain synchrony in cooperative and competitive contexts have suggested that

64 competition might be at the very end of this continuum, with evidence for stronger interbrain synchrony

65 during cooperation compared to competition found using EEG (Chuang & Hsu, 2023; Sinha et al.,

66 2016) and (functional) Near-Infrared Spectroscopy (fNIRS) (Cui et al., 2012; Lu et al., 2019). For

67 example, Sinha et al., 2016 used a computerised pong game to show increased interbrain synchrony

68 when participants played as a team against the computer program, compared to when participants played

69 against one another (Sinha et al., 2016). The authors suggested that the difference in interbrain

70 synchrony could in part be explained by participants having different strategies to defeat the opponent

71 in the competition condition. Another study revealed interbrain coupling during cooperation and

72 interbrain decoupling during competition when comparing true teams to shuffled team labels (Chuang

73 & Hsu, 2023). Together, these results suggest that enhanced interbrain synchrony in cooperative

74 compared to competitive settings could be driven by shared representations of one's own and others'

75 actions, intentions, strategies, goals, etc. during cooperation, that are not present during competition.

76 However, these studies do not directly provide insight into what information about self and

77 other is represented in the neural signal during competitive scenarios. Here we leverage multivariate

78 analysis methods on electroencephalography (EEG) hyperscanning data to investigate how the human

79 brain encodes self- and other-related information during the Rock-Paper-Scissors game to better

80 understand the cognitive processes supporting decision performance during real-time interaction in a

81 competitive context. Importantly, hyperscanning enabled the investigation of the processes behind

82 winning or losing in the Rock-Paper-Scissors game, as it requires studying the cognitive and neural

83 dynamics of the two players together in interaction. Moreover, the use of multivariate analyses on

84 hyperscanning data allowed going beyond interbrain synchrony to more directly track neural

85 representations related to self and other within interacting brains, consistent with the argument that

86 understanding the neural bases of social interactions with hyperscanning requires analysis at multiple

87 levels, between but also within brains (Zamm et al., 2024).

88 The Rock-Paper-Scissors game is a widely used model for studying social interaction in a competitive

89 context, where wins, losses, or draws have equal probability for each player. The optimal strategy for

90 both players is to be as random, and therefore unpredictable, as possible (West & Lebiere, 2001; Zhou,

91 2016). However, humans rarely achieve randomness (Figurska et al., 2008; Neuringer, 1986; Treisman

92 & Faulkner, 1987) and instead, biases or strategies emerge during this game (Dyson, 2019). This

93 includes over-selection of one option — typically Rock — adopting outcome-based strategies such as

94 the 'win-stay, lose-shift' strategy, or employing cycle-based strategies, where players rotate through the

95 options (Dyson, 2019). Humans are generally poor at being random, as evidenced by recurring patterns

96 in the way we move, and decisions and errors we make (Figurska et al., 2008; Miyata et al., 2017; Riley

97 & Turvey, 2002; Torre et al., 2013; Varlet & Richardson, 2015; Zhu et al., 2022), although this depends

98 on the task and feedback (Guseva et al., 2023; Neuringer, 1986; Nickerson, 2002; Riley & Turvey,

99   2002; Varlet et al., 2012). By combining the Rock-Paper-Scissors game with decoding methods on EEG

100 data, we can track the neural information about participant's decisions, as well as the expected decisions

101 of their opponent and information about the previous choices of self and other. Therefore, this game

102 can serve as a useful model to investigate the neural processes underlying strategic decision-making in

103 a competitive context that requires randomness.

104   Recent hyperscanning studies using fNIRS reported increased interbrain synchrony while

105 participants played Rock-Paper-Scissors compared to rest, with effects observed in the right dorsolateral

106 prefrontal cortex (Kayhan et al., 2022; Zhang et al., 2024), as well as the left dorsolateral prefrontal

107 cortex and temporo-parietal junction (Kayhan et al., 2022). However, when using the more stringent

108 comparison of playing the game alone, rather than rest, only the right temporo-parietal junction showed

109 increased interbrain synchrony during the joint task (Kayhan et al., 2022). This suggests that observed

110 effects in some areas could be driven largely by shared response-related processes (Burgess, 2013;

111 Holroyd, 2022; Varlet & Grootswagers, 2024). In addition, interbrain synchrony levels did not increase

112 when participants made explicit predictions about the outcome, aiming for either the same (cooperative

113 condition) or a different (competitive condition) outcome as the other player, compared to when

114 participants made implicit predictions (free play) (Kayhan et al., 2022). This suggests that interbrain

115 synchrony was not sensitive to explicitly making predictions about the likely action of the other player

116 and leaves open questions about the role of prediction in social decision-making contexts. As interbrain

117 synchrony methods are activation-based, they cannot directly measure what information related to the

118 decision or prediction is encoded in the brain. In this study, we leverage multivariate analysis methods

119 as a powerful alternative (Moerel et al., 2025; Varlet & Grootswagers, 2024; Zada et al., 2024),

120 combining these methods with the high temporal resolution of EEG hyperscanning to specifically

121 capture self-other decision-related information within each player's brain at different task stages during

122 competitive social interactions. Specifically, for each participant, we assess the time-course of the

123 presence of neural information about 1) the response decision of the participant, 2) the prediction about

124 the likely response of the opponent, and 3) the knowledge about previous events, related to both self

125 and other. Furthermore, these neural representations were compared between overall match winners

126 and losers to understand how they might drive success.

127   We tested 31 pairs of participants playing a computerised version of the classic Rock-Paper-

128 Scissors game. We recorded 64-channel EEG, while each pair played 480 games total. Behavioural

129 results corroborated previous research, showing that participant's responses were not fully random,

130 even though randomness is the best strategy in this competitive game (Glover & Dixon, 2017; West &

131 Lebiere, 2001; Zhou, 2016). Multivariate decoding methods on the EEG signals revealed the neural

132 encoding of players' own decisions in the current trial. Additionally, information about the participant's

133 own decision on the previous trial, as well as that of the opponent, was also encoded in the neural signal

134 – but only for individuals who lost the overall match, suggesting that maintaining prior-trial information

135 could have potentially hindered performance. These findings provide new insights into self-other neural

136 processes supporting decision-making and the influence of cognitive biases and priors in competitive

137 social settings.

138

139 **2. RESULTS**

140 **2.1. Behavioural strategies and biases**

141 We continuously recorded 64-channel EEG data from 62 participants, grouped into 31 pairs, using the

142 BioSemi Active-Two electrode system (BioSemi, Amsterdam, The Netherlands). Participants were

143 seated at a computer in separate rooms and played 480 games of a computerised version of the Rock-

144 Paper-Scissors game. In each game, both players choose between Rock, Paper, or Scissors. The

145 outcome of the game was determined by three rules (Figure 1A): Rock beats Scissors, Scissors beat

146 Paper, and Paper beats Rock. If both players choose the same response, the game is a tie. For each

147 player, wins, losses, or draws therefore have equal probability. An overview of the experiment is shown

148 in Figure 1B. Each game consisted of three phases: Decision (2 s), Response (2 s) and Feedback (1 s),

149 which allowed a stage-wise analysis of information in the EEG responses time-locked to each stage

150 without interference from future stages (Moerel et al., 2024). During the Decision phase, the participants

151 could decide which response to select. During the Response phase, participants selected their response

152 (Rock, Paper, or Scissors), and during the Feedback phase, the outcome of the game was displayed.

153 The behavioural results revealed that selected responses were not completely random and that

154 biases and strategies across players varied. Figure 1C shows the distribution of the three possible game

155 outcomes for each pair: the overall match winner wins the game, the overall match winner loses the

156 game, and the game is a tie. The overall match winner is defined as the person with the greatest number

157 of wins out of the full 480 games. The distribution across pairs shows that although there was a clear

158 winner for some pairs, the overall match winner and loser performed very similar in many pairs. Figure

159 1D shows the distribution of how often the most, mid, and least chosen responses are played. The closer

160 to 33.3%, the less bias there was. The data illustrate that there was a spread in participants' bias towards

161 one option. The pie charts in Figure 1D show separately for the most, mid, and least chosen responses

162 the proportion of *Rock*, *Paper*, and *Scissors* responses. In line with previous work (Dyson et al., 2016;

163 Forder & Dyson, 2016; Wang et al., 2014; Xu et al., 2013), there was a bias towards Rock, 51.61% of

164 participants had Rock as their most played response, followed by Paper (33.87%). Only 14.52% of

165 participants had Scissors as their most played response. We also assessed the change between two

166 consecutive responses, with a completely random player having a 33.3% chance of playing the same

167 response twice in a row. Figure 1E shows the chance of a game-to-game response change, split by the

168 outcome of the previous game. Many participants were biased towards changing their response,

169 regardless of the outcome of the previous game. Finally Figure 1F shows the predictability of each

170 player, as obtained via a Markov chain using various number of previous games. An accuracy of 33.3%

171 means the responses of the player are completely unpredictable, which would be the best strategy. The

172 data show that most participants were not completely unpredictable, as the Markov chain accuracy was

173   above chance. These findings highlight a variation in participants' strategies and responses, revealing

174   individual biases.

175

176   **2.2. Neural decoding of player and opponent decisions**

177   We used linear discriminant analysis classifiers to investigate if there was information in the

178   EEG signal about 1) the response made by the player, 2) the response made by the other player, 3) the

179   player's response in the prior trial, and 4) the response of the other player in the prior trial. We did this

180   separately for each 250 ms time bin and each participant using a 10-fold cross validation (Grootswagers

181   et al., 2017). We divided the data into 10 folds (i.e. subsets), trained the classifier using the data from

182   all-but-one subset, and tested on the left-out subset. We repeated this 10 times, leaving out a different

183   subset each time. We removed no-response trials and created 20 pseudo trials for each fold and response

184   by averaging 4 trials belonging to the same fold and response type before decoding to enhance the signal

185   to noise ratio (Grootswagers et al., 2017; Scrivener et al., 2023). For the channel searchlight, we

186   repeated the same analysis for each individual channel and 4 to 5 neighbouring channels, to obtain

187   topographies of the decoding accuracy. The results are shown in Figure 2 and provide evidence that

188   information about the player's own response was encoded in the EEG signal during the Decision phase

189   (max BF = 57) as well as the Response phase (max BF = 729,735) and the Feedback phase (max BF =

190   16,028), as indicated by the Bayes Factors. There was no information about the other player's response

191   during the Decision and Response phases, suggesting the players were not able to determine the likely

192   response of their opponent above chance. However, the EEG signal contained information about the

193   other player's response during the Feedback phase (max BF = 87,847), likely reflecting the visually

194   presented feedback about the response of their opponent. In addition, there was evidence that the

195   player's own previous response was encoded during the Decision phase (max BF = 8), and anecdotal

196   evidence during the Response phase (max BF = 4), suggesting that information about the previous

197   response could be used during the decision-making on the current trials. Finally, there was information

198   about the other player's previous response during the Decision phase (max BF = 16,659), suggesting

199   this information was incorporated in the decision about which move to play. These results show the

200   data contain information about the player's current and previous decisions, as well as information about

201   the previous decisions of the other player. Moreover, the topographies show that the encoding of current

202   and previous decisions during the Decision and Response phases is driven by distributed responses

203   across the brain. This contrasts with the Feedback phase, where we see a strong contribution of posterior

204   channels to the above chance decoding, in line with more visually driven responses, as participants

205   receive visually presented feedback about their own, as well as their opponent's response. These spatial

206   distributions are in line with the decoding accuracies in the Decision and Response phases being driven

207   by decision-related information.

208   To assess whether the information that was present in the brain was modulated by whether the

209   player won or lost over the entire experiment, we split the decoding accuracies for the overall match

210 winners and losers (Figure 3). The player's own response was encoded in the EEG signal during the

211 Response and Feedback phases for both winners (max BF = 573) and losers (max BF = 3,337). Both

212 groups showed neural information about the other player's response during the Feedback phase only.

213 Importantly, the results indicated that only losers showed neural encoding of their own previous

214 response during the Response phase (max BF = 11), and of the other player's previous response during

215 the Decision phase (max BF = 2,382). Although inter-group Bayes Factors did not provide direct

216 evidence of strong differences between winners and losers – indeed, most Bayes Factors showed

217 evidence for no difference between these groups, which could be explained by the scores of the winners

218 and losers being often very close – our results nevertheless suggest that losers encoded self and other

219 information from previous trials, whereas winners did not.

220

3. DISCUSSION

222 In this study, we investigated how the brain encodes self-other decision-related information during the

223 competitive Rock-Paper-Scissors game. In line with previous research our participants did not act fully

224 random, even though unpredictability is the best strategy in this competitive game (Glover & Dixon,

225 2017; West & Lebiere, 2001; Zhou, 2016). There were variations between players, but Rock was

226 generally over-selected and Scissors under-selected. This finding has been widely observed in previous

227 work (Dyson et al., 2016; Forder & Dyson, 2016; Wang et al., 2014; Xu et al., 2013). In addition,

228 participants switched their response from trial-to-trial in a more or less predictable way, regardless of

229 whether they won or lost on the previous trial. These behavioural biases have been observed previously

230 in this game (Dyson, 2019), and are in line with other work that suggests people are not able to

231 consciously generate random actions (Figurska et al., 2008; Issartel et al., 2007; Neuringer, 1986;

232 Treisman & Faulkner, 1987).

233 EEG hyperscanning data revealed that there was neural information about the player's own

234 current response during all phases of the task, driven by the decision the participant had to make. This

235 information was already present in the Decision phase, before the participant was asked to respond,

236 suggesting we were able to track the decision-making of the participant as it unfolded in real-time.

237 There was no above-chance decoding of the opponent's decision during the Decision or Response

238 phases. This suggests that at the level of the group, participants could not reliably predict the next move

239 of their opponent. This finding fits with the previous hyperscanning literature, that found weaker

240 interbrain synchrony during competition compared to cooperation (Cui et al., 2012; Lu et al., 2019;

241 Sinha et al., 2016), as well as evidence for interbrain coupling during cooperation and interbrain

242 decoupling during competition when comparing true teams to shuffled team labels (Chuang & Hsu,

243 2023). This suggests that during cooperation, participants may form a shared representation of goals,

244 intentions, or actions of self and other, facilitated by behavioural predictability. However, during

245 competition, behavioural unpredictability is advantageous (Glover & Dixon, 2017; Vesper et al., 2011),

246 potentially driving a reduction in shared representations and therefore interbrain synchrony. Our results

247　indeed showed that participants were too unpredictable for their opponents to reliably encode their next

248　move. Finally, above chance decoding of the previous responses of self and other show that the brain

249　actively encodes knowledge about previous trials during the Decision phase of the current trial. In

250　determining their response on the current game, participants likely rely on what their opponent played,

251　and to a lesser extent, what they themselves played in the previous game. This study adds to the findings

252　from the hyperscanning literature by directly assessing the content of the neural representations about

253　self and other, enabling us to distinguish between neural information about decisions, expectations

254　about the opponent, and knowledge about previous interactions.

255　　　　To gain insight into the neural representations that may underlie successful versus unsuccessful

256　competitive behaviour, we tracked self- and other-related neural representations within the brains of

257　winners compared to losers. While decoding results split by overall match winners and losers showed

258　no differences in brain coding of decision-related information, we did find a different signature of

259　decoding results between the two groups. Small differences in wins and losses in some pairs suggest

260　that chance, not strategy, determined the winner, likely adding noise and obscuring potential group

261　differences. Specifically, we found that whereas we could track the decision-making on the current trial

262　for both the winners and losers, only the overall match losers encoded information about what they

263　played themselves and what the other player chose on the previous trial. This suggests that losers likely

264　incorporated information about the previous game, whereas this was not the case for the overall match

265　winners. This reliance on previous responses, both of self and other, might hinder these participants, as

266　the best strategy is to be as random, and therefore unpredictable, as possible (Glover & Dixon, 2017;

267　West & Lebiere, 2001; Zhou, 2016). By comparing the individual neural representations of winners and

268　losers, rather than focusing on interbrain synchrony, this study provides more direct insight into which

269　self- and other-related representations are associated with a competitive advantage.

270　　　　Previous work on the Rock-Paper-Scissors game has used fNIRS to investigate prediction-

271　related processes (Kayhan et al., 2022; Zhang et al., 2024). Although the results showed increased

272　interbrain synchrony during the interactive task compared to playing the game alone, this measure did

273　not increase when making explicit predictions (Kayhan et al., 2022). Previous work has also found

274　increased interbrain synchrony in various regions when playing the game compared to rest (Kayhan et

275　al., 2022; Zhang et al., 2024), but these findings could be driven by shared response-related processes

276　(Burgess, 2013; Holroyd, 2022; Varlet & Grootswagers, 2024). In a recent study, Varlet and

277　Grootswagers (2024) showed that interbrain synchrony measures are not sensitive to the information

278　contained in the neural data. To address this, they introduced Interbrain RSA, a multivariate analysis

279　method designed to assess the alignment of information across participants' neural signals. Building on

280　this, we used decoding, a complementary multivariate approach (Grootswagers et al., 2017), to show

281　that we can track the decision-related information about the responses of the participant and their

282　opponent at different stages in the task. While the limited response options in our design precluded the

283　use of Interbrain RSA, we show that decoding methods are highly effective in capturing decision-related

284 neural information, highlighting the potential of this method for hyperscanning research as an extension

285 of Interbrain RSA (Moerel et al., 2025; Varlet & Grootswagers, 2024). Unlike interbrain synchrony

286 measures, which often rely on control conditions where participants are at rest or do not interact, the

287 decoding method in this study leverages direct comparisons of neural activation associated with distinct

288 response options. This makes decoding less susceptible to confounds such as shared visual or response-

289 related information, offering a promising method to study neural processes underpinning real-time

290 social interactions, in both cooperative and competitive settings, including in atypical populations

291 (Charman, 2003; Coey et al., 2012; MacRitchie et al., 2017; Moreau et al., 2024; Raffard et al., 2015;

292 Sebanz et al., 2006; Varlet et al., 2014; Zhang et al., 2024).

293   In conclusion, multivariate pattern analyses of EEG hyperscanning data enabled us to reveal

294 how the human brain encodes self-other decision-related information over time during a competitive

295 Rock-Paper-Scissors game. Despite the optimal strategy being randomness, players displayed critical

296 behavioural biases and predictable strategies. EEG data showed neural encoding of current decisions,

297 with overall match losers uniquely relying on past trials, potentially hindering performance. These

298 findings highlight the challenge of overcoming cognitive biases and reliance on prior outcomes for

299 effective decision-making during competitive social interaction.

300

4. METHODS

4.1. Participants

303 Sixty-eight participants, grouped into 34 pairs, took part in the EEG study at Western Sydney

304 University. Three EEG datasets were excluded from the analysis: two datasets had an issue with CMS

305 which resulted in no EEG data for one of the players, and another dataset did not contain triggers. The

306 sample included in this dataset consisted of 31 pairs (62 participants). Participants in this sample were

307 38 females / 22 males / 2 non-binary, 55 right-handed / 6 left-handed / 1 ambidextrous, mean age 27.85

308 years, SD = 6.73 years, range 18 – 47 years. All participants reported normal or corrected-to-normal

309 vision. The EEG session took approximately 2 hours in total to complete, and participants received a

310 payment of $60 AUD. The study was approved by the Human Ethics Committee of the University of

311 Western Sydney, and all participants provided written informed consent (H13092).

312

4.2. Stimuli and experiment

314 During the experiment, the two participants in each pair played a computerised version of the

315 competitive Rock-Paper-Scissors game. Participants were seated behind a computer screen in separate

316 rooms. In each game, both players choose between Rock, Paper, or Scissors. The outcome of the game

317 is determined by three rules (Figure 1B): Rock beats Scissors, Scissors beat Paper, and Paper beats

318 Rock. If both players choose the same response, the game is a tie. For each player, wins, losses, or

319 draws therefore have equal probability.

320   An overview of the experiment is shown in Figure 1C. Each game consisted of three phases:

321   Decision (2 s), Response (2 s) and Feedback (1 s), allowing us to assess decision-related information in

322   the EEG signal at each stage without interference from future stages (Moerel et al., 2024). The Decision

323   screen consisted of a central fixation cross and a prompt to "Make a decision". During this phase, the

324   participants could decide which response to select. During the Response phase, participants saw a

325   prompt to "Select your response", and the three options were displayed as a cartoon of the hand shapes

326   associated with the game (Figure 1A); Rock was displayed as a fist, Paper as an open hand, and Scissors

327   as a fist with the index and middle fingers extended, forming a V. The order of the Rock, Paper and

328   Scissors images was chosen at random for each participant and each block but stayed the same for all

329   games within a block. During this phase, participants used a 3-button box to select their response. The

330   order of the three stimuli on the screen indicated the mapping between the buttons and responses, and

331   the response mapping therefore changed between blocks. This means that taking together the data from

332   the whole experiment, the EEG signal was minimally contaminated by motor preparation and/or

333   execution signals. The Response screen automatically timed out after 2 s, even if no response was given

334   by one or both of the participants. The Response phase was followed by the Feedback phase, where the

335   outcome of the game was displayed for 1 s. Participants saw the response of player 1 on the left of the

336   screen, and the response of player 2 on the right of the screen. If no response was given, "No Response"

337   was displayed. The outcome was displayed above the response images, as "Player 1 wins", "Player 2

338   wins", or "Draw". If one of the participants did not respond, the other participant won the game.

339   The experiment consisted of 480 games of Rock-Paper-Scissors, divided into 12 blocks of 40

340   games, and took approximately 45 minutes to complete. The experiment was displayed on a mid-grey

341   background using a VIEWPixx monitor at 120 Hz, using custom C++ code. Participants were seated

342   approximately 60 cm from the screen. The images were displayed at 324 by 324 pixels (approximate

343   8.20 by 8.20 degrees of visual angle) and the fixation cross was 54 by 54 pixels (approximate 1.37 by

344   1.37 degrees of visual angle).

345

346   **4.3. EEG acquisition and pre-processing**

347   We collected continuous EEG data from 64 channels, digitised at a sampling rate of 2048 Hz, using the

348   BioSemi Active-Two electrode system (BioSemi, Amsterdam, The Netherlands). Electrode placement

349   followed the international 10-20 system (Oostenveld & Praamstra, 2001). The dataset consists of the

350   raw EEG data as well as pre-processed data. We applied the following pre-processing steps, using the

351   FieldTrip toolbox (version 20240110) in MATLAB (Oostenveld et al., 2011). First, we re-referenced

352   the data to the common average, and epoched the data from 200 ms before the onset of the Decision

353   screen to 5000 ms after the onset of the Decision screen. The onset of each trial, in seconds as well as

354   samples, can be found in the events.tsv file. We did not apply filtering, as this has been shown to cause

355   artefacts or temporally smear the signal (Delorme, 2023; Grootswagers et al., 2017; van Driel et al.,

356   2021). We identified noisy channels through visual inspection, which can also be found in the

357   participants.tsv file. We interpolated noisy channels based on neighbouring channels, using the

358   *ft_channelrepair* function with a distance measure of 0.5 cm. We then down-sampled the data to 256

359   Hz. Finally, we made three separate epochs for each trial, locked to the onset of the Decision screen (-

360   200 ms – 2000 ms), Response screen (-200 ms – 2000 ms), and Feedback screen (-200 ms – 1000 ms)

361   respectively. We applied baseline corrections for each separate epoch, using the window from -200 m

362   to 0 ms, locked to the screen onset. We then averaged the resulting data into 250 ms time bins, resulting

363   in a total of 20 time bins for the 0 to 5000 ms time-course.

364

365   **4.4. Behavioural analysis**

366   To examine the behavioural responses recorded during the EEG session, we performed the following

367   analyses. To assess the difference in performance between winners and losers, we obtained the

368   distribution of game outcomes across pairs, categorising results as wins for the overall match winner,

369   wins for the overall match loser, or ties. We examined the response bias by analysing how frequently

370   the most, mid, and least chosen responses were played. To explore this further, we looked at the

371   proportion of Rock, Paper, and Scissors responses separately for the most, mid, and least chosen

372   responses. Additionally, we assessed the distribution of response changes between consecutive

373   responses, split by the outcome of the previous game. Finally, we used a Markov chain model (Norris,

374   1998) with varying window sizes (5 to 100 previous games, in steps of 1) to predict each player's most

375   likely response. We then calculated the prediction accuracy as a measure of response predictability for

376   each participant. Together, these analyses provide insight into the strategies, response biases, and

377   predictability of the participants.

378

379   **4.5. Decoding analysis**

380   We used a time-varying brain decoding analysis (Grootswagers et al., 2017) implemented using the

381   CoSMoMVPA toolbox (version 1.1.0) (Oosterhof et al., 2016) to determine whether there was

382   information about the response decisions made by the player and opponent, based on the raw activation

383   values across the 64 EEG channels. Specifically, we used a regularised ($\lambda = 0.01$) linear discriminant

384   analysis (LDA) classifier to determine if there was information about 1) the response made by the

385   player, 2) the response made by the other player, 3) the player's response in the prior trial, and 4) the

386   response of the other player in the prior trial. We opted for this classifier as it provides a good balance

387   between performance and computational requirements (Grootswagers et al., 2017; Guggenmos et al.,

388   2018). Before decoding, we removed no-response trials and made 20 pseudo trials for each fold and

389   response (Rock, Paper, or Scissors) by averaging 4 trials of the same fold and response to enhance the

390   signal to noise ratio (Grootswagers et al., 2017; Scrivener et al., 2023). We then trained a linear classifier

391   to distinguish between the different classes of interest (e.g. the different responses made by the player)

392   based on the pattern of activation across all 64 EEG channels. We used the EEG channel voltages,

393   separate for each trial and time bin, as features for the decoding. We did this separately for each

individual participant. We used a 10-fold cross validation, where we split the dataset into 10 parts (i.e. folds). We trained the linear classifier on the data from 9 of those folds and then tested the classifier performance on the left-out fold. We did this in an iterative fashion, where each fold was left out as a test fold once. We then calculated the classifier accuracy, separately for each individual participant and time bin, by determining the percentage of times the classifier predicted the correct class (e.g. response is rock). We calculated the decoding accuracy separately for each of the 3 possible responses and then averaged these measures to obtain the decoding accuracy for each time bin. If the classification accuracy is higher than would be predicted by chance, we can say that there is information in the neural response about the condition that is decoded. To ensure that motor signals were not a reliable signal for the classifier, distinguishing between the different response options during the Response phase, we changed the response button mapping between blocks. A given response option (e.g. Rock) was therefore associated with all response buttons in the training data. In addition, the mapping between the responses and buttons differed between the participants in the dyad, which means any similarity in responses between individuals in the dyad would not translate into similarities in motor preparation or execution. Together, these measures eliminated the chance of motor contamination in the decoding. For the channel searchlight, we repeated the same analysis above for individual clusters of channels. Each cluster consisted of the main channel and 4 or 5 neighbouring channels.

4.6. Statistics

To determine whether there was evidence for above chance decoding of decision-related information, we used Bayesian statistics (Dienes, 2011; Kass & Raftery, 1995; Morey et al., 2016; Rouder et al., 2009; Wagenmakers, 2007), with the Bayes Factor R package (Morey & Rouder, 2018). To calculate the Bayes Factors, we applied Bayesian directional t-tests for each time bin. We used the method described by Teichmann and colleagues (2022), using a null interval between $d = 0$ and $d = 0.5$ to exclude small effect sizes. To calculate Bayes Factors for the difference between the overall match winners and losers, we used a two-tailed t-test.

5. CODE AND DATA AVAILABILITY

All analysis codes, figures, and an example dataset are publicly available via the Open Science Framework (https://doi.org/10.17605/OSF.IO/YJXKN). The data are named and organised according to the BIDS standard (Gorgolewski et al., 2016; Pernet et al., 2019). The full dataset will be made publicly available upon publication.

6. ACKNOWLEDGMENTS

431

7. DECLARATION OF CONFLICT OF INTEREST

None declared.

8. REFERENCES

Babiloni, F., Astolfi, L., Cincotti, F., Mattia, D., Tocci, A., Tarantino, A., Marciani, MG., Salinari, S., Gao, S., Colosimo, A., & De Vico Fallani, F. (2007). Cortical Activity and Connectivity of Human Brain during the Prisoner's Dilemma: An EEG Hyperscanning Study. *2007 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 4953–4956. https://doi.org/10.1109/IEMBS.2007.4353452

Balconi, M., & Vanutelli, M. E. (2017). Cooperation and competition with hyperscanning methods: Review and future application to emotion domain. *Frontiers in Computational Neuroscience*, *11*, 86.

Burgess, A. P. (2013). On the interpretation of synchronization in EEG hyperscanning studies: A cautionary note. *Frontiers in Human Neuroscience*, *7*. https://doi.org/10.3389/fnhum.2013.00881

Charman, T. (2003). Why is joint attention a pivotal skill in autism? *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, *358*(1430), 315–324. https://doi.org/10.1098/rstb.2002.1199

Cheng, S., Wang, J., Luo, R., & Hao, N. (2024). Brain to brain musical interaction: A systematic review of neural synchrony in musical activities. *Neuroscience & Biobehavioral Reviews*, 105812.

Chuang, C.-H., & Hsu, H.-C. (2023). Pseudo-mutual gazing enhances interbrain synchrony during remote joint attention tasking. *Brain and Behavior*, *13*(10), e3181. https://doi.org/10.1002/brb3.3181

Coey, C. A., Varlet, M., & Richardson, M. J. (2012). Coordination dynamics in a socially situated nervous system. *Frontiers in Human Neuroscience*, *6*, 164.

Cui, X., Bryant, D. M., & Reiss, A. L. (2012). NIRS-based hyperscanning reveals increased interpersonal coherence in superior frontal cortex during cooperation. *NeuroImage*, *59*(3), 2430–2437. https://doi.org/10.1016/j.neuroimage.2011.09.003

Czeszumski, A., Eustergerling, S., Lang, A., Menrath, D., Gerstenberger, M., Schuberth, S., Schreiber, F., Rendon, Z. Z., & König, P. (2020). Hyperscanning: A Valid Method to Study Neural Inter-brain Underpinnings of Social Interaction. *Frontiers in Human Neuroscience*, *14*. https://doi.org/10.3389/fnhum.2020.00039

Delorme, A. (2023). EEG is better left alone. *Scientific Reports*, *13*(1), 2372. https://doi.org/10.1038/s41598-023-27528-0

467 Dienes, Z. (2011). Bayesian Versus Orthodox Statistics: Which Side Are You On? *Perspectives on*
468   *Psychological Science*, *6*(3), 274–290. https://doi.org/10.1177/1745691611406920

469 Dumas, G., Nadel, J., Soussignan, R., Martinerie, J., & Garnero, L. (2010). Inter-brain
470   synchronization during social interaction. *PloS One*, *5*(8), e12166.

471 Dyson, B. J. (2019). Behavioural Isomorphism, Cognitive Economy and Recursive Thought in Non-
472   Transitive Game Strategy. *Games*, *10*(3), Article 3. https://doi.org/10.3390/g10030032

473 Dyson, B. J., Wilbiks, J. M. P., Sandhu, R., Papanicolaou, G., & Lintag, J. (2016). Negative outcomes
474   evoke cyclic irrational decisions in Rock, Paper, Scissors. *Scientific Reports*, *6*(1), 20479.
475   https://doi.org/10.1038/srep20479

476 Fallani, F. D. V., Nicosia, V., Sinatra, R., Astolfi, L., Cincotti, F., Mattia, D., Wilke, C., Doud, A.,
477   Latora, V., He, B., & Babiloni, F. (2010). Defecting or Not Defecting: How to "Read" Human
478   Behavior during Cooperative Games by EEG Measurements. *PLOS ONE*, *5*(12), e14187.
479   https://doi.org/10.1371/journal.pone.0014187

480 Figurska, M., Stańczyk, M., & Kulesza, K. (2008). Humans cannot consciously generate random
481   numbers sequences: Polemic study. *Medical Hypotheses*, *70*(1), 182–185.
482   https://doi.org/10.1016/j.mehy.2007.06.038

483 Forder, L., & Dyson, B. J. (2016). Behavioural and neural modulation of win-stay but not lose-shift
484   strategies as a function of outcome value in Rock, Paper, Scissors. *Scientific Reports*, *6*(1),
485   33809. https://doi.org/10.1038/srep33809

486 Glover, S., & Dixon, P. (2017). The role of predictability in cooperative and competitive joint action.
487   *Journal of Experimental Psychology: Human Perception and Performance*, *43*(4), 644–650.
488   https://doi.org/10.1037/xhp0000362

489 Gorgolewski, K. J., Auer, T., Calhoun, V. D., Craddock, R. C., Das, S., Duff, E. P., Flandin, G.,
490   Ghosh, S. S., Glatard, T., Halchenko, Y. O., Handwerker, D. A., Hanke, M., Keator, D., Li,
491   X., Michael, Z., Maumet, C., Nichols, B. N., Nichols, T. E., Pellman, J., … Poldrack, R. A.
492   (2016). The brain imaging data structure, a format for organizing and describing outputs of
493   neuroimaging experiments. *Scientific Data*, *3*(1), 160044.
494   https://doi.org/10.1038/sdata.2016.44

495 Grootswagers, T., Wardle, S. G., & Carlson, T. A. (2017). Decoding Dynamic Brain Patterns from
496   Evoked Responses: A Tutorial on Multivariate Pattern Analysis Applied to Time Series
497   Neuroimaging Data. *Journal of Cognitive Neuroscience*, *29*(4), 677–697.
498   https://doi.org/10.1162/jocn_a_01068

499 Guggenmos, M., Sterzer, P., & Cichy, R. M. (2018). Multivariate pattern analysis for MEG: A
500   comparison of dissimilarity measures. *NeuroImage*, *173*, 434–447.
501   https://doi.org/10.1016/j.neuroimage.2018.02.044

502 Guseva, M., Bogler, C., Allefeld, C., & Haynes, J.-D. (2023). Instruction effects on randomness in
503   sequence generation. *Frontiers in Psychology*, *14*.
504   https://doi.org/10.3389/fpsyg.2023.1113654

505 Holroyd, C. B. (2022). Interbrain synchrony: On wavy ground. *Trends in Neurosciences*, *45*(5), 346–
506   357. https://doi.org/10.1016/j.tins.2022.02.002

507 Hu, Y., Pan, Y., Shi, X., Cai, Q., Li, X., & Cheng, X. (2018). Inter-brain synchrony and cooperation
508   context in interactive decision making. *Biological Psychology*, *133*, 54–62.
509   https://doi.org/10.1016/j.biopsycho.2017.12.005

510 Issartel, J., Marin, L., & Cadopi, M. (2007). Unintended interpersonal co-ordination:"can we march to
511   the beat of our own drum?" *Neuroscience Letters*, *411*(3), 174–179.

512 Kass, R. E., & Raftery, A. E. (1995). Bayes Factors. *Journal of the American Statistical Association*,
513   *90*(430), 773–795. https://doi.org/10.1080/01621459.1995.10476572

514 Kayhan, E., Nguyen, T., Matthes, D., Langeloh, M., Michel, C., Jiang, J., & Hoehl, S. (2022).
515   Interpersonal neural synchrony when predicting others' actions during a game of rock-paper-
516   scissors. *Scientific Reports*, *12*(1), 12967. https://doi.org/10.1038/s41598-022-16956-z

517 Keller, P. E., Novembre, G., & Hove, M. J. (2014). Rhythm in joint action: Psychological and
518   neurophysiological mechanisms for real-time interpersonal coordination. *Philosophical*
519   *Transactions of the Royal Society B: Biological Sciences*, *369*(1658), 20130394.
520   https://doi.org/10.1098/rstb.2013.0394

521 Krumhuber, E. G., Skora, L. I., Hill, H. C., & Lander, K. (2023). The role of facial movements in
522   emotion recognition. *Nature Reviews Psychology*, *2*(5), 283–296.

523 Lehmann, K., Bolis, D., Friston, K. J., Schilbach, L., Ramstead, M. J. D., & Kanske, P. (2023). An
524   Active-Inference Approach to Second-Person Neuroscience. *Perspectives on Psychological*
525   *Science*, 17456916231188000. https://doi.org/10.1177/17456916231188000

526 Lu, K., Xue, H., Nozawa, T., & Hao, N. (2019). Cooperation Makes a Group be More Creative.
527   *Cerebral Cortex*, *29*(8), 3457–3470. https://doi.org/10.1093/cercor/bhy215

528 MacRitchie, J., Varlet, M., & Keller, P. E. (2017). Embodied expression through entrainment and co-
529   representation in musical ensemble performance. In *The Routledge companion to embodied*
530   *music interaction* (pp. 150–159). Routledge.
531   https://www.taylorfrancis.com/chapters/edit/10.4324/9781315621364-17/embodied-
532   expression-entrainment-co-representation-musical-ensemble-performance-jennifer-
533   macritchie-manuel-varlet-peter-keller

534 McMahon, E., & Isik, L. (2023). Seeing social interactions. *Trends in Cognitive Sciences*.
535   https://www.cell.com/trends/cognitive-sciences/fulltext/S1364-6613(23)00248-6

536 Miyata, K., Varlet, M., Miura, A., Kudo, K., & Keller, P. E. (2017). Modulation of individual
537   auditory-motor coordination dynamics through interpersonal visual coupling. *Scientific*
538   *Reports*, *7*(1), 16220.

539   Moerel, D., Grootswagers, T., Quek, G. L., Smit, S., & Varlet, M. (2025). Information alignment

540   between interacting brains. *bioRxiv*, 2025.01.07.631802.

541   https://doi.org/10.1101/2025.01.07.631802

542   Moerel, D., Rich, A. N., & Woolgar, A. (2024). Selective attention and decision-making have

543   separable neural bases in space and time. *Journal of Neuroscience*.

544   https://doi.org/10.1523/JNEUROSCI.0224-24.2024

545   Moreau, Q., Brun, F., Ayrolles, A., Nadel, J., & Dumas, G. (2024). Distinct social behavior and inter-

546   brain connectivity in Dyads with autistic individuals. *Social Neuroscience*, *19*(2), 124–136.

547   https://doi.org/10.1080/17470919.2024.2379917

548   Morey, R. D., Romeijn, J.-W., & Rouder, J. N. (2016). The philosophy of Bayes factors and the

549   quantification of statistical evidence. *Journal of Mathematical Psychology*, *72*, 6–18.

550   https://doi.org/10.1016/j.jmp.2015.11.001

551   Morey, R. D., & Rouder, J. N. (2018). *BayesFactor: Computation of Bayes Factors for Common*

552   *Designs*. https://CRAN.R-project.org/package=BayesFactor

553   Nam, C. S., Choo, S., Huang, J., & Park, J. (2020). Brain-to-Brain Neural Synchrony During Social

554   Interactions: A Systematic Review on Hyperscanning Studies. *Applied Sciences*, *10*(19),

555   Article 19. https://doi.org/10.3390/app10196669

556   Neuringer, A. (1986). Can people behave "randomly?": The role of feedback. *Journal of*

557   *Experimental Psychology: General*, *115*(1), 62–75. https://doi.org/10.1037/0096-

558   3445.115.1.62

559   Nickerson, R. (2002). The Production and Perception of Randomness. *Psychological Review*, *109*,

560   330–357. https://doi.org/10.1037/0033-295X.109.2.330

561   Norris, J. R. (1998). *Markov Chains*. Cambridge University Press.

562   Oosterhof, N. N., Connolly, A. C., & Haxby, J. V. (2016). CoSMoMVPA: Multi-Modal Multivariate

563   Pattern Analysis of Neuroimaging Data in Matlab/GNU Octave. *Frontiers in*

564   *Neuroinformatics*, *10*. https://doi.org/10.3389/fninf.2016.00027

565   Pernet, C. R., Appelhoff, S., Gorgolewski, K. J., Flandin, G., Phillips, C., Delorme, A., & Oostenveld,

566   R. (2019). EEG-BIDS, an extension to the brain imaging data structure for

567   electroencephalography. *Scientific Data*, *6*(1), 103. https://doi.org/10.1038/s41597-019-0104-

568   8

569   Raffard, S., Salesse, R. N., Marin, L., Del-Monte, J., Schmidt, R. C., Varlet, M., Bardy, B. G.,

570   Boulenger, J.-P., & Capdevielle, D. (2015). Social priming enhances interpersonal

571   synchronization and feeling of connectedness towards schizophrenia patients. *Scientific*

572   *Reports*, *5*(1), 8156.

573   Redcay, E., & Schilbach, L. (2019). Using second-person neuroscience to elucidate the mechanisms

574   of social interaction. *Nature Reviews Neuroscience*, *20*(8), 495–505.

575   https://doi.org/10.1038/s41583-019-0179-4

576 Riley, M. A., & Turvey, M. T. (2002). Variability and Determinism in Motor Behavior. *Journal of*
577   *Motor Behavior*, *34*(2), 99–125. https://doi.org/10.1080/00222890209601934

578 Rouder, J. N., Speckman, P. L., Sun, D., Morey, R. D., & Iverson, G. (2009). Bayesian t tests for
579   accepting and rejecting the null hypothesis. *Psychonomic Bulletin & Review*, *16*(2), 225–237.
580   https://doi.org/10.3758/PBR.16.2.225

581 Scrivener, C. L., Grootswagers, T., & Woolgar, A. (2023). Optimising analysis choices for
582   multivariate decoding: Creating pseudotrials using trial averaging and resampling. *BioRXiv*,
583   2023–10.

584 Sebanz, N., Bekkering, H., & Knoblich, G. (2006). Joint action: Bodies and minds moving together.
585   *Trends in Cognitive Sciences*, *10*(2), 70–76.

586 Sinha, N., Maszczyk, T., Wanxuan, Z., Tan, J., & Dauwels, J. (2016). EEG hyperscanning study of
587   inter-brain synchrony during cooperative and competitive interaction. *2016 IEEE*
588   *International Conference on Systems, Man, and Cybernetics (SMC)*, 004813–004818.
589   https://doi.org/10.1109/SMC.2016.7844990

590 Teichmann, L., Moerel, D., Baker, C. I., & Grootswagers, T. (2022). An empirically-driven guide on
591   using Bayes Factors for M/EEG decoding. *Aperture Neuro*, *1*(8), 1–10.
592   https://doi.org/10.1101/2021.06.23.449663

593 Tognoli, E., Lagarde, J., DeGuzman, G. C., & Kelso, J. A. S. (2007). The phi complex as a
594   neuromarker of human social coordination. *Proceedings of the National Academy of Sciences*,
595   *104*(19), 8190–8195. https://doi.org/10.1073/pnas.0611453104

596 Toppi, J., Borghini, G., Petti, M., He, E. J., Giusti, V. D., He, B., Astolfi, L., & Babiloni, F. (2016).
597   Investigating Cooperative Behavior in Ecological Settings: An EEG Hyperscanning Study.
598   *PLOS ONE*, *11*(4), e0154236. https://doi.org/10.1371/journal.pone.0154236

599 Torre, K., Varlet, M., & Marmelat, V. (2013). Predicting the biological variability of environmental
600   rhythms: Weak or strong anticipation for sensorimotor synchronization? *Brain and Cognition*,
601   *83*(3), 342–350.

602 Treisman, M., & Faulkner, A. (1987). Generation of random sequences by human subjects: Cognitive
603   operations or psychological process? *Journal of Experimental Psychology: General*, *116*(4),
604   337–355. https://doi.org/10.1037/0096-3445.116.4.337

605 van Driel, J., Olivers, C. N. L., & Fahrenfort, J. J. (2021). High-pass filtering artifacts in multivariate
606   classification of neural time series data. *Journal of Neuroscience Methods*, *352*, 109080.
607   https://doi.org/10.1016/j.jneumeth.2021.109080

608 Varlet, M., & Grootswagers, T. (2024). Measuring information alignment in hyperscanning research
609   with representational analyses: Moving beyond interbrain synchrony. *Frontiers in Human*
610   *Neuroscience*, *18*. https://doi.org/10.3389/fnhum.2024.1385624

611　Varlet, M., Marin, L., Capdevielle, D., Del-Monte, J., Schmidt, R. C., Salesse, R. N., Boulenger, J.-P.,

612　　　　Bardy, B. G., & Raffard, S. (2014). Difficulty leading interpersonal coordination: Towards an

613　　　　embodied signature of social anxiety disorder. *Frontiers in Behavioral Neuroscience*, *8*, 29.

614　Varlet, M., Marin, L., Issartel, J., Schmidt, R. C., & Bardy, B. G. (2012). *Continuity of visual and*

615　　　　*auditory rhythms influences sensorimotor coordination*.

616　　　　https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0044082

617　Varlet, M., Nozaradan, S., Nijhuis, P., & Keller, P. E. (2020). Neural tracking and integration of

618　　　　'self' and 'other' in improvised interpersonal coordination. *Neuroimage*, *206*, 116303.

619　Varlet, M., & Richardson, M. J. (2015). What would be Usain Bolt's 100-meter sprint world record

620　　　　without Tyson Gay? Unintentional interpersonal synchronization between the two sprinters.

621　　　　*Journal of Experimental Psychology: Human Perception and Performance*, *41*(1), 36–41.

622　　　　https://doi.org/10.1037/a0038640

623　Vesper, C., van der Wel, R. P. R. D., Knoblich, G., & Sebanz, N. (2011). Making oneself predictable:

624　　　　Reduced temporal variability facilitates joint action coordination. *Experimental Brain*

625　　　　*Research*, *211*(3), 517–530. https://doi.org/10.1007/s00221-011-2706-z

626　Wagenmakers, E.-J. (2007). A practical solution to the pervasive problems ofp values. *Psychonomic*

627　　　　*Bulletin & Review*, *14*(5), 779–804. https://doi.org/10.3758/BF03194105

628　Wang, Z., Xu, B., & Zhou, H.-J. (2014). Social cycling and conditional responses in the Rock-Paper-

629　　　　Scissors game. *Scientific Reports*, *4*(1), 5830. https://doi.org/10.1038/srep05830

630　West, R. L., & Lebiere, C. (2001). Simple games as dynamic, coupled systems: Randomness and

631　　　　other emergent properties. *Cognitive Systems Research*, *1*(4), 221–239.

632　　　　https://doi.org/10.1016/S1389-0417(00)00014-0

633　Xu, B., Zhou, H.-J., & Wang, Z. (2013). Cycle frequency in standard Rock–Paper–Scissors games:

634　　　　Evidence from experimental economics. *Physica A: Statistical Mechanics and Its*

635　　　　*Applications*, *392*(20), 4997–5005. https://doi.org/10.1016/j.physa.2013.06.039

636　Zada, Z., Goldstein, A., Michelmann, S., Simony, E., Price, A., Hasenfratz, L., Barham, E., Zadbood,

637　　　　A., Doyle, W., Friedman, D., Dugan, P., Melloni, L., Devore, S., Flinker, A., Devinsky, O.,

638　　　　Nastase, S. A., & Hasson, U. (2024). A shared model-based linguistic space for transmitting

639　　　　our thoughts from brain to brain in natural conversations. *Neuron*, S0896-6273(24)00460-4.

640　　　　https://doi.org/10.1016/j.neuron.2024.06.025

641　Zamm, A., Loehr, J. D., Vesper, C., Konvalinka, I., Kappel, S. L., Heggli, O. A., Vuust, P., & Keller,

642　　　　P. E. (2024). A practical guide to EEG hyperscanning in joint action research: From

643　　　　motivation to implementation. *Social Cognitive and Affective Neuroscience*, *19*(1), nsae026.

644　Zhang, Y., Ye, W., Yin, J., Wu, Q., Huang, Y., Hao, N., Cui, L., Zhang, M., & Cai, D. (2024).

645　　　　Exploring the role of mutual prediction in inter-brain synchronization during competitive

646　　　　interactions: An fNIRS hyperscanning investigation. *Cerebral Cortex*, *34*(1), bhad483.

647　　　　https://doi.org/10.1093/cercor/bhad483

648   Zhou, H.-J. (2016). The rock–paper–scissors game. *Contemporary Physics*, *57*(2), 151–163.

649   https://doi.org/10.1080/00107514.2015.1026556

650   Zhu, J.-Q., León-Villagrá, P., Chater, N., & Sanborn, A. N. (2022). Understanding the structure of

651   cognitive noise. *PLoS Computational Biology*, *18*(8), e1010312.

652

653

654   **9. FIGURE LEGEND LIST**

655   **Figure 1. Task overview and behavioural responses. A)** The rules of the game as shown to the

656   participants. Rock beats Scissors, Scissors beat Paper, and Paper beats Rock. The three options are

657   displayed as a cartoon of the hand shapes associated with the game. Rock was displayed as a fist, Paper

658   as an open hand, and Scissors as a fist with the index and middle fingers extended. Images were sourced

659   online from www.dreamstime.com. **B)** Each game consisted of three phases. In the Decision phase (left

660   panel), participants saw a fixation cross with the prompt to "Make a decision" for 2 seconds. In the

661   Response phase (middle panel), participants saw the three options with a prompt to "Select your

662   response". The order of the three options was randomised for each participant and block. Participants

663   used the buttons on a button box to select their response. In the Feedback phase (right panel),

664   participants received feedback about the response of player 1 on the left and player 2 on the right.

665   Feedback about the outcome was displayed above as "Player 1 wins", "Player 2 wins", or "Draw". The

666   feedback was shown for 1 second. **C)** The distribution of the three possible game outcomes over pairs:

667   the overall match winner wins (left), the overall match winner loses (middle), and draw (right). The

668   white line on the box plot shows the median, each dot shows one pair. Theoretical chance is 33.3%. **D)**

669   The raincloud plots show the distribution of how often the most, mid, and least chosen responses are

670   played. The closer to 33.3%, the less bias there is. The dots show individual participants instead of

671   pairs. The pie charts above show for each response frequency (most, mid, and least chosen) the

672   proportion of Rock, Paper, and Scissors responses: 51.61% of participants had Rock as their most

673   played response, followed by Paper (33.87%), and Scissors (14.52%). **E)** The percentage of games

674   where the response changes across two consecutive games, split by the outcome of the previous game:

675   after a win (left), loss (middle), or draw (right). All plotting conventions are the same as in Figure 1C,

676   but theoretical chance is 66.7%. **F)** The accuracy of a Markov chain in predicting which response a

677   player will make. This can be used as a measure of how predictable the responses of the participants

678   are. The x-axis shows the different window sizes of the Markov chain. Grey lines show individual

679   participants, the thick blue line shows the group average and the shaded area around the group average

680   shows the 95% confidence interval. Theoretical chance is 33.3%.

681

682   **Figure 2. EEG decoding accuracy of the player's own responses and those of their opponent.** The

683   plotting conventions are the same for all four plots showing the classification accuracy over time for

684   the three phases: Decision (0 – 2 s, orange), Response (2 – 4 s, red), and Feedback (4 – 5 s, purple).

685   Decoding accuracies are obtained for 250 ms time bins. We used a linear classifier to determine whether

686   there was information in the pattern across the EEG channels about **A)** the response the player chose **B)**

687   the response played by the opponent, **C)** the response the player chose on the previous trial, and **D)** the

688   response the opponent chose on the previous trial. The Bayes Factors are shown below the plot on a

689   logarithmic scale. Bayes Factors below 1 are plotted in blue colours and show evidence for chance

690   decoding, and Bayes Factors above 1 are plotted in red colours and show evidence for above chance

691   decoding, with the colour intensity reflecting the evidence for either hypothesis. The topographies,

692   based on a channel searchlight, are shown below the Bayes Factors. We obtained a topography for each

693   250 ms time bin in the decoding and then collapsed across 1-second time bins. Lighter colours reflect

694   higher decoding accuracies.

695

696   **Figure 3. EEG decoding accuracy of the player's own responses and those of their opponent, split**

697   **by overall match winners and losers.** The plotting conventions are the same as in Figure 2. We split

698   the decoding accuracies presented in Figure 2 by overall match winners (blue) and losers (green). We

699   determined whether there is information in the pattern across the EEG channels about **A)** the response

700   selected by the player, **B)** the response made by the other player, **C)** the player's response in the previous

701   trial, and **D)** the other player's response in the previous trial.
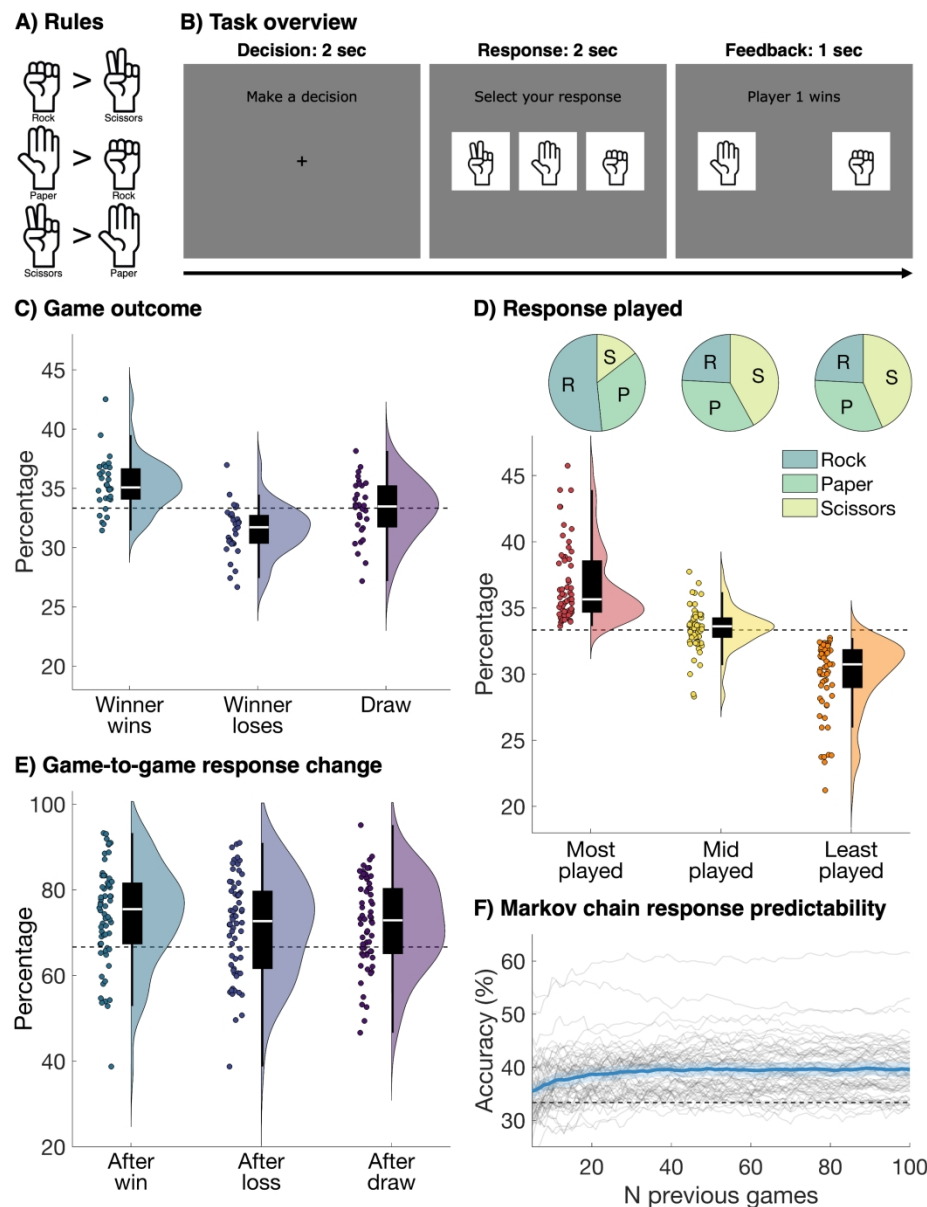
702

Figure 1. Task overview and behavioural responses. A) The rules of the game as shown to the participants. Rock beats Scissors, Scissors beat Paper, and Paper beats Rock. The three options are displayed as a cartoon of the hand shapes associated with the game. Rock was displayed as a fist, Paper as an open hand, and Scissors as a fist with the index and middle fingers extended. Images were sourced online from www.dreamstime.com. B) Each game consisted of three phases. In the Decision phase (left panel), participants saw a fixation cross with the prompt to "Make a decision" for 2 seconds. In the Response phase (middle panel), participants saw the three options with a prompt to "Select your response". The order of the three options was randomised for each participant and block. Participants used the buttons on a button box to select their response. In the Feedback phase (right panel), participants received feedback about the response of player 1 on the left and player 2 on the right. Feedback about the outcome was displayed above as "Player 1 wins", "Player 2 wins", or "Draw". The feedback was shown for 1 second. C) The distribution of the three possible game outcomes over pairs: the overall match winner wins (left), the overall match winner loses (middle), and draw (right). The white line on the box plot shows the median, each dot shows one pair. Theoretical chance is 33.3%. D) The raincloud plots show the distribution of how often the most, mid, and

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

least chosen responses are played. The closer to 33.3%, the less bias there is. The dots show individual participants instead of pairs. The pie charts above show for each response frequency (most, mid, and least chosen) the proportion of Rock, Paper, and Scissors responses: 51.61% of participants had Rock as their most played response, followed by Paper (33.87%), and Scissors (14.52%). E) The percentage of games where the response changes across two consecutive games, split by the outcome of the previous game: after a win (left), loss (middle), or draw (right). All plotting conventions are the same as in Figure 1C, but theoretical chance is 66.7%. F) The accuracy of a Markov chain in predicting which response a player will make. This can be used as a measure of how predictable the responses of the participants are. The x-axis shows the different window sizes of the Markov chain. Grey lines show individual participants, the thick blue line shows the group average and the shaded area around the group average shows the 95% confidence interval. Theoretical chance is 33.3%.
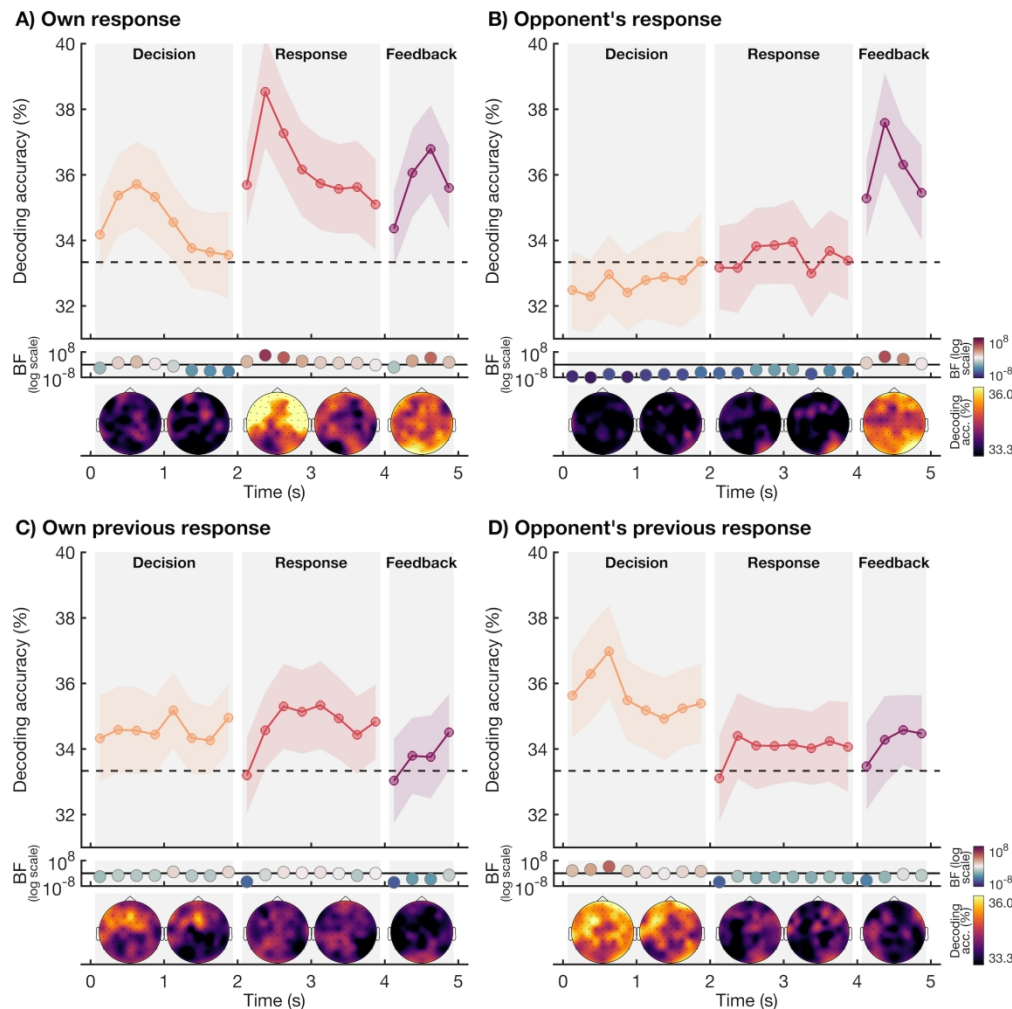
511x668mm (149 x 149 DPI)

Figure 2. EEG decoding accuracy of the player's own responses and those of their opponent. The plotting conventions are the same for all four plots showing the classification accuracy over time for the three phases: Decision (0 – 2 s, orange), Response (2 – 4 s, red), and Feedback (4 – 5 s, purple). Decoding accuracies are obtained for 250 ms time bins. We used a linear classifier to determine whether there was information in the pattern across the EEG channels about A) the response the player chose B) the response played by the opponent, C) the response the player chose on the previous trial, and D) the response the opponent chose on the previous trial. The Bayes Factors are shown below the plot on a logarithmic scale. Bayes Factors below 1 are plotted in blue colours and show evidence for chance decoding, and Bayes Factors above 1 are plotted in red colours and show evidence for above chance decoding. Darker colours reflect stronger evidence for either hypothesis. The topographies, based on a channel searchlight, are shown below the Bayes Factors. We obtained a topography for each 250 ms time bin in the decoding and then collapsed across 1-second time bins. Lighter colours reflect higher decoding accuracies.
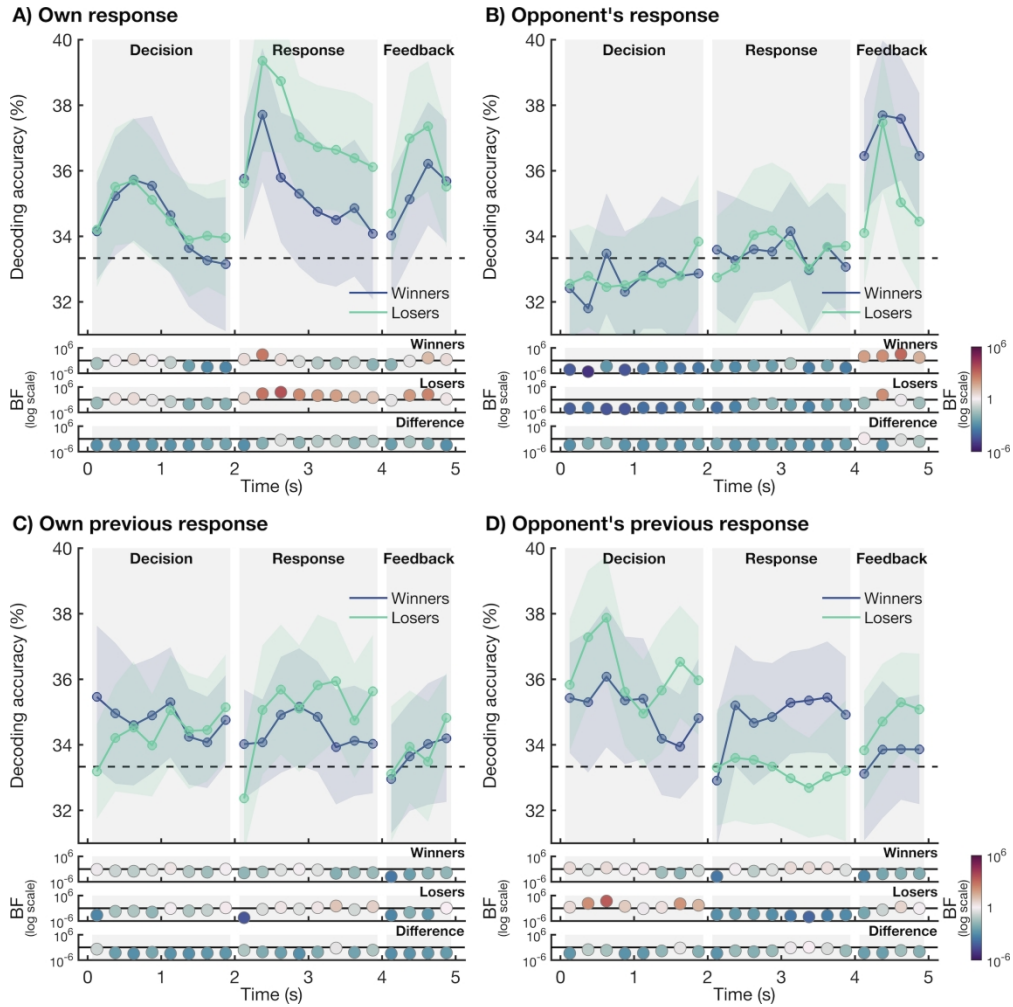
952x950mm (72 x 72 DPI)

Figure 3. EEG decoding accuracy of the player's own responses and those of their opponent, split by overall match winners and losers. The plotting conventions are the same as in Figure 2. We split the decoding accuracies presented in Figure 2 by overall match winners (blue) and losers (green). We determined whether there is information in the pattern across the EEG channels about A) the response selected by the player, B) the response made by the other player, C) the player's response in the previous trial, and D) the other player's response in the previous trial.

952x949mm (72 x 72 DPI)