Neural decoding of competitive decision-making in Rock-Paper-Scissors using EEG hyperscanning

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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 mostly focused on cooperative tasks and remains limited in competitive contexts. Here, we obtained electroencephalography (EEG) hyperscanning data for 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, we found that neural signals contained information about decisions made by participants during gameplay, revealing certain strategies. Notably, losers showed unique reliance on prior trials, suggesting memory-based strategies that may impair optimal performance. These results reveal how competitive decision-making is shaped by cognitive biases and memory of 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 (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). Hyperscanning has been used to advance 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; Sinha et al., 2016), leaving the neural processes underpinning performance in such activities – equally important for everyday social interactions – unclear. 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). Here we leverage multivariate analysis methods on electroencephalography (EEG) hyperscanning data to investigate how the human brain encodes self- and other-related information during the Rock-Paper-Scissors game to better understand the neuropsychological processes supporting performance in competitive contexts.

The Rock-Paper-Scissors game is a widely used model for studying social interaction in a competitive context, where wins, losses, or draws have equal probability for each player. The optimal strategy for both players is to be as random, and therefore unpredictable, as possible (West & Lebiere, 2001; Zhou, 2016). However, humans rarely achieve randomness (Figurska et al., 2008; Neuringer, 1986; Treisman & Faulkner, 1987) and instead, biases or strategies emerge during this game (Dyson, 2019). This includes over-selection of one option — typically Rock — adopting outcome-based strategies such as the 'win-stay, lose-shift' strategy, or employing cycle-based strategies, where players rotate through the options (Dyson, 2019). Humans are generally poor at being random, as evidenced by recurring patterns in the way we move, and decisions and errors we make (Figurska et al., 2008; Miyata et al., 2017; Riley & Turvey, 2002; Torre et al., 2013; Varlet & Richardson, 2015; Zhu et al., 2022), although this depends on the task and feedback (Guseva et al., 2023; Neuringer, 1986; Nickerson, 2002; Riley & Turvey, 2002; Varlet et al., 2012). The Rock-Paper-Scissors game can serve as a useful model to investigate strategic decision-making in a competitive context that requires randomness.

Recent hyperscanning studies using functional near-infrared spectroscopy (fNIRS) reported increased interbrain synchrony while participants played Rock-Paper-Scissors compared to rest, with effects observed in the right dorsolateral prefrontal cortex (Kayhan et al., 2022; Zhang et al., 2024), as well as the left dorsolateral prefrontal cortex and temporo-parietal junction (Kayhan et al., 2022). However, when using the more stringent comparison of playing the game alone, rather than rest, only the right temporo-parietal junction showed increased interbrain synchrony during the joint task (Kayhan et al., 2022). This suggests that observed effects in some areas could be driven largely by shared response-related processes (Burgess, 2013; Holroyd, 2022; Varlet & Grootswagers, 2024). In addition, interbrain synchrony levels did not increase when participants made explicit predictions about the outcome, aiming for either the same (cooperative condition) or a different (competitive condition) outcome as the other player, compared to when participants made implicit predictions (free play) (Kayhan et al., 2022). This suggests that interbrain synchrony was not sensitive to explicitly making predictions about the likely action of the other player and leaves open questions about the role of prediction in social decision-making contexts. As interbrain synchrony methods are activation-based, they cannot directly measure what information related to the decision or prediction is encoded in the brain. In this study, we leverage multivariate analysis methods as a powerful alternative (Moerel et al., 2025; Varlet & Grootswagers, 2024; Zada et al., 2024), combining these methods with the high temporal resolution of EEG to specifically capture self-other decision-related information at different task stages during competitive social interactions.

We tested 31 pairs of participants playing a computerised version of the classic Rock-Paper-Scissors game. We recorded 64-channel EEG, while each pair played 480 games total. Behavioural results corroborated previous research, showing that participant's responses were not fully random, even though randomness is the best strategy in this competitive game (Glover & Dixon, 2017; West & Lebiere, 2001; Zhou, 2016). Multivariate decoding methods on the EEG signals revealed the neural encoding of players' own decisions in the current trial. Self-made decisions, as well as those made by the opponent, in the previous trial were also encoded but for losers only, potentially hindering their performance. These findings provide new insights into self-other neural processes supporting decision-making and the influence of cognitive biases and priors in competitive social settings.

2. RESULTS

2.1. Behavioural strategies and biases

We continuously recorded 64-channel EEG data from 62 participants, grouped into 31 pairs, using the BioSemi Active-Two electrode system (BioSemi, Amsterdam, The Netherlands). Participants were seated at a computer in separate rooms and played 480 games of a computerised version of the Rock-Paper-Scissors game. In each game, both players choose between Rock, Paper, or Scissors. The outcome of the game was determined by three rules (Figure 1A): Rock beats Scissors, Scissors beat Paper, and Paper beats Rock. If both players choose the same response, the game is a tie. For each player, wins, losses, or draws therefore have equal probability. An overview of the experiment is shown in Figure 1B. Each game consisted of three phases: Decision (2 s), Response (2 s) and Feedback (1 s), which allowed a stage-wise analysis of information in the EEG responses time-locked to each stage without interference from future stages (Moerel et al., 2024). During the Decision phase, the participants could decide which response to select. During the Response phase, participants selected their response (Rock, Paper, or Scissors), and during the Feedback phase, the outcome of the game was displayed.

The behavioural results revealed that selected responses were not completely random and that biases and strategies across players varied. Figure 1C shows the distribution of the three possible game outcomes for each pair: the overall match winner wins the game, the overall match winner loses the game, and the game is a tie. The overall match winner is defined as the person with the greatest number of wins out of the full 480 games. The distribution across pairs shows that although there was a clear winner for some pairs, the overall match winner and loser performed very similar in many pairs. Figure 1D shows the distribution of how often the most, mid, and least chosen responses are played. The closer to 33.3%, the less bias there was. The data illustrate that there was a spread in participants' bias towards one option. The pie charts in Figure 1D show separately for the most, mid, and least chosen responses the proportion of *Rock*, *Paper*, and *Scissors* responses. In line with previous work (Dyson et al., 2016; Forder & Dyson, 2016; Wang et al., 2014; Xu et al., 2013), there was a bias towards Rock, 51.61% of participants had Rock as their most played response, followed by Paper (33.87%). Only 14.52% of participants had Scissors as their most played response. We also assessed the change between two consecutive responses, with a completely random player having a 33.3% chance of playing the same response twice in a row. Figure 1E shows the chance of a game-to-game response change, split by the outcome of the previous game. Many participants were biased towards changing their response, regardless of the outcome of the previous game. Finally Figure 1F shows the predictability of each player, as obtained via a Markov chain using various number of previous games. An accuracy of 33.3% means the responses of the player are completely unpredictable, which would be the best strategy. The data show that most participants were not completely unpredictable, as the Markov chain accuracy was above chance. These findings highlight a variation in participants' strategies and responses, revealing individual biases.

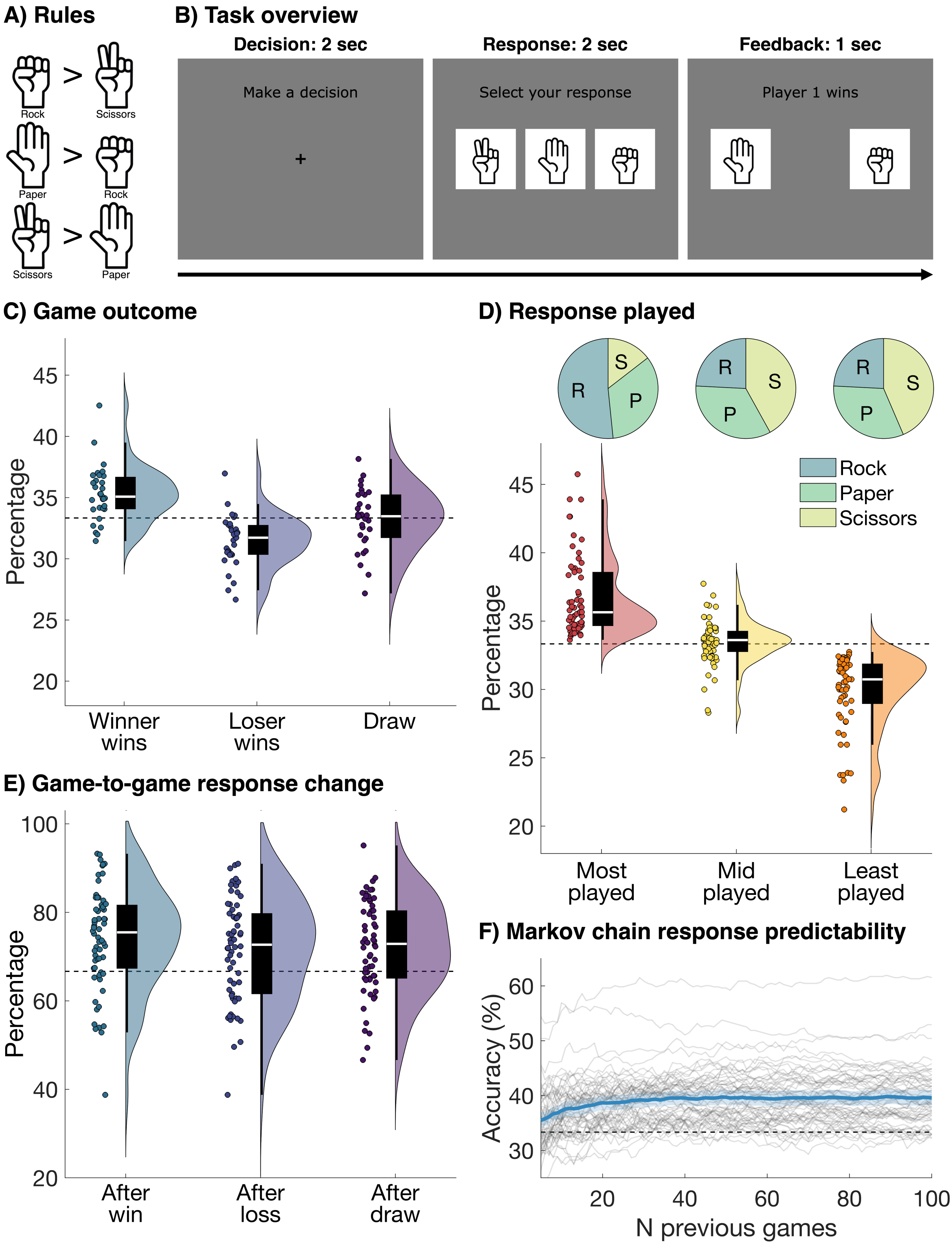

Figure 1. Task overview and behavioural responses. A) The rules of the game as shown to the participants. Rock beats Scissors, Scissors beat Paper, and Paper beats Rock. The three options are displayed as a cartoon of the hand shapes associated with the game. Rock was displayed as a fist, Paper as an 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 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%.

2.2. Neural decoding of player and opponent decisions

We used linear discriminant analysis classifiers to investigate if there was information in the EEG signal about 1) the response made by the player, 2) the response made by the other player, 3) the player's response in the prior trial, and 4) the response of the other player in the prior trial. We did this separately for each 250 ms time bin and each participant using a 10-fold cross validation (Grootswagers et al., 2017). We divided the data into 10 folds (i.e. subsets), trained the classifier using the data from all-but-one subset, and tested on the left-out subset. We repeated this 10 times, leaving out a different subset each time. We removed no-response trials and created 20 pseudo trials for each fold and response by averaging 4 trials belonging to the same fold and response type before decoding to enhance the signal to noise ratio (Grootswagers et al., 2017; Scrivener et al., 2023). For the channel searchlight, we repeated the same analysis for each individual channel and 4 to 5 neighbouring channels, to obtain topographies of the decoding accuracy. The results are shown in Figure 2 and provide evidence that information about the player's own response was encoded in the EEG signal during the Decision phase (max BF = 57) as well as the Result phase (max BF = 729,735) and the Feedback phase (max BF = 16,028), as indicated by the Bayes Factors. There was no information about the other player's response during the Decision and Response phases, suggesting the players were not able to determine the likely response of their opponent above chance. However, the EEG signal contained information about the other player's response during the Feedback phase. In addition, there was evidence that the player's own previous response was encoded during the Decision phase (max BF = 8), and anecdotal evidence during the Response phase (max BF = 4), suggesting that information about the previous response could be used during the decision-making on the current trials. Finally, there was information about the other player's previous response during the Decision phase (max BF = 16,659), suggesting this information was incorporated in the decision about which move to play. These results show the data contain information about the player's current and previous decisions, as well as information about the previous decisions of the other player. Moreover, the topographies show that the encoding of current and previous decisions during the Decision and Response phases is driven by distributed responses across the brain. This contrasts with the feedback phase, where we see distributions in line with more visually driven responses, as participants receive visually presented feedback about their own, as well as their opponent's response. These spatial distributions are in line with the decoding accuracies in the Decision and Response phases being driven by decision-related information.

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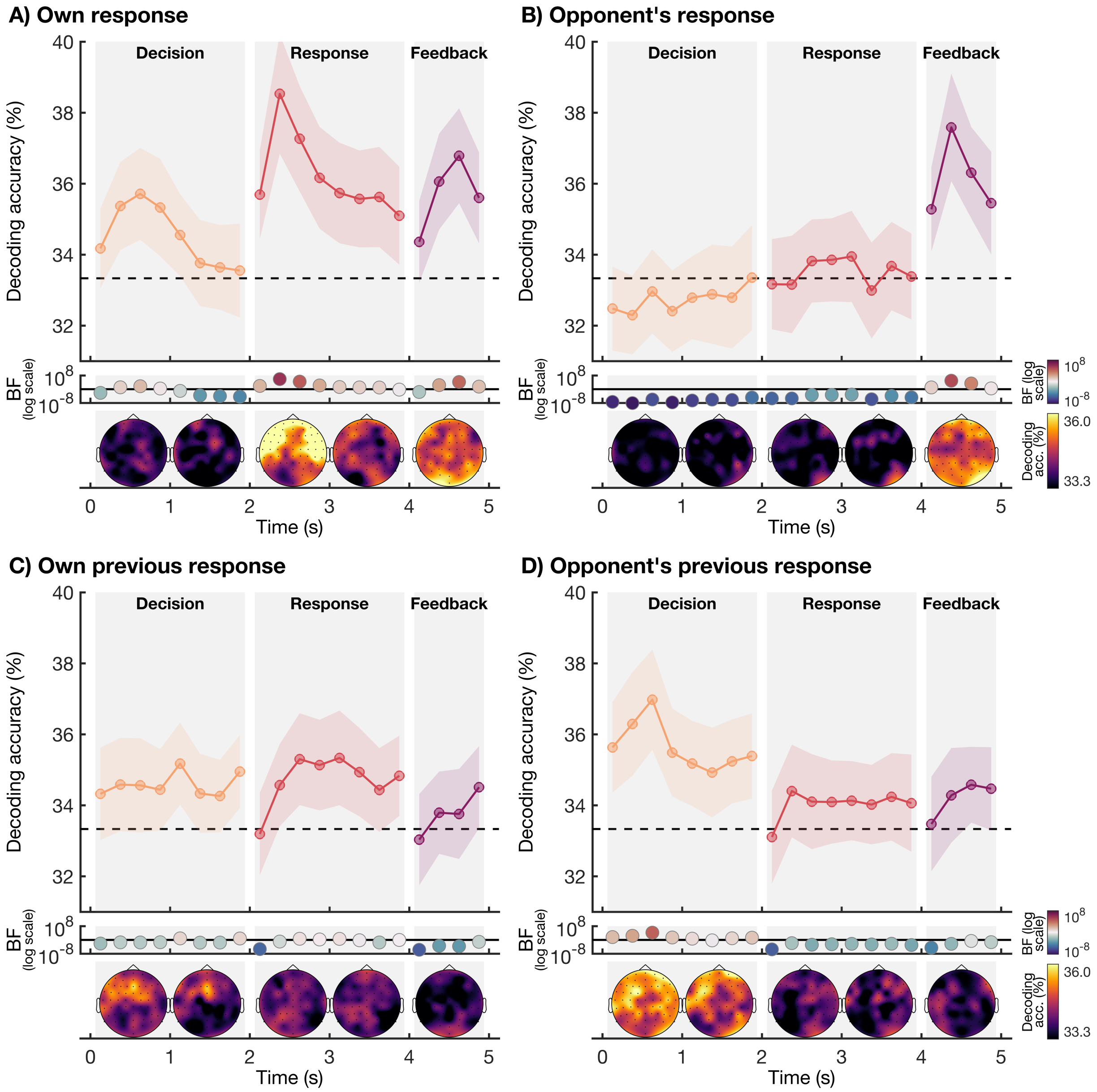

Figure 2. EEG decoding accuracy of the player's own responses and those of their opponent. The plotting conventions are the same for all four plots showing the classification accuracy over time for the three phases: Decision (0 – 2 s, orange), Response (2 – 4 s, red), and Feedback (4 – 5 s, purple). 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.

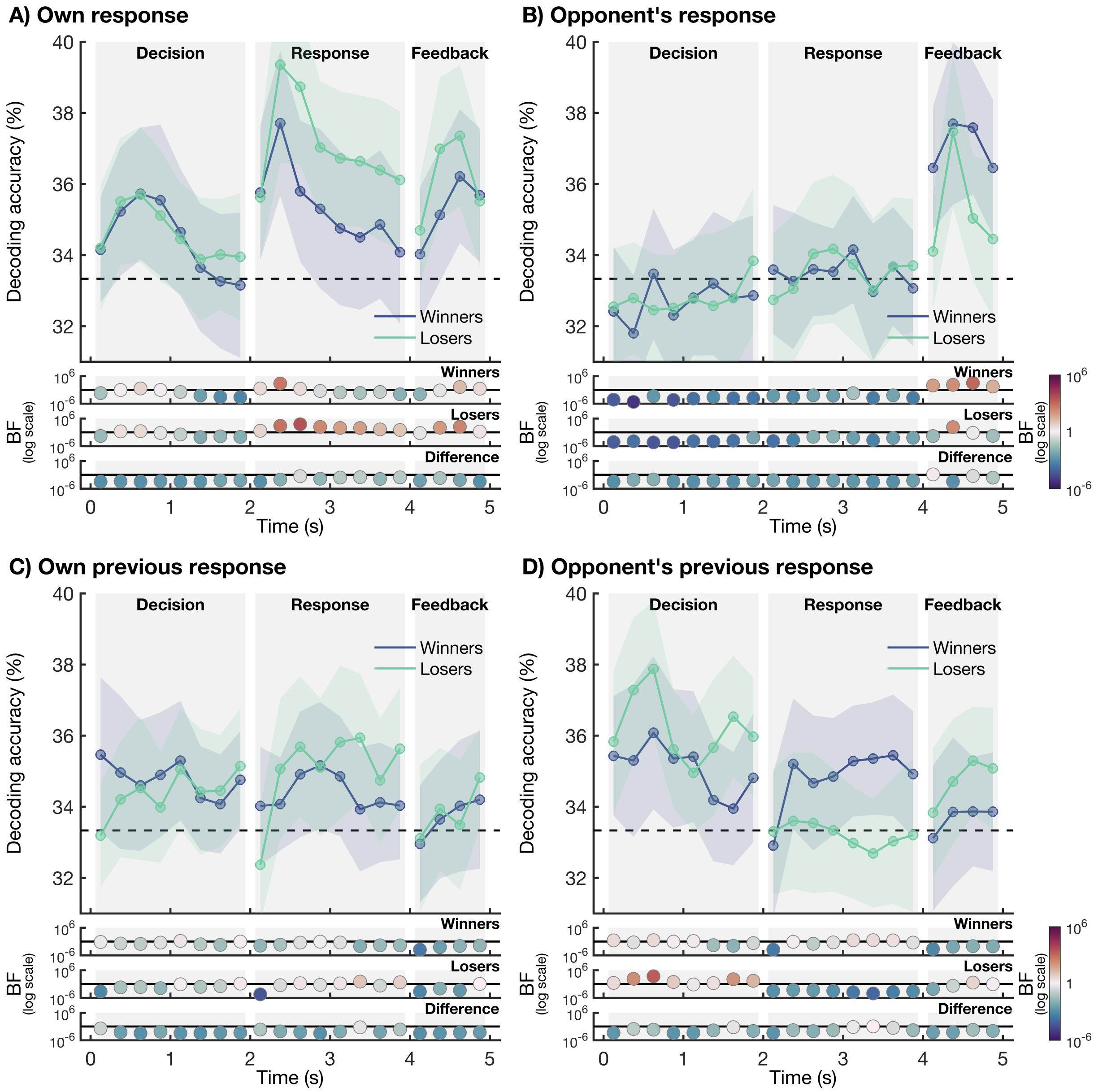

Figure 3. EEG decoding accuracy of the player's own responses and those of their opponent, split by overall match winners and losers. The plotting conventions are the same as in Figure 2. We split the decoding accuracies presented in Figure 2 by overall match winners (blue) and losers (green). We determined 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.

To assess whether the information that was present in the brain was modulated by whether the player won or lost over the entire experiment, we split the decoding accuracies for the overall match winners and losers (Figure 3). The player's own response was encoded in the EEG signal during the Response and Feedback phases for both winners (max BF = 573) and losers (max BF = 3,337). Both groups showed neural information about the other player's response during the Feedback phase only. Importantly, the results indicated that only losers showed neural encoding of their own previous response during the Response phase (max BF = 11), and of the other player's previous response during the Decision phase (max BF = 2,382). While inter-group Bayes Factors did not provide direct evidence of differences between winners and losers, with most Bayes Factors showing evidence for no difference, which could be explained by the scores of the winners and losers being often very close, these results do suggest that losers encoded self and other information from previous trials, whereas winners did not.

3. DISCUSSION

In this study, we investigated how the brain encodes self-other decision-related information during the competitive Rock-Paper-Scissors game. In line with previous research our participants did not act fully random, even though unpredictability is the best strategy in this competitive game (Glover & Dixon, 2017; West & Lebiere, 2001; Zhou, 2016). There were variations between players, but Rock was generally over-selected and Scissors under-selected. This finding has been widely observed in previous work (Dyson et al., 2016; Forder & Dyson, 2016; Wang et al., 2014; Xu et al., 2013). In addition, participants switched their response from trial-to-trial in a more or less predictable way, regardless of whether they won or lost on the previous trial. These behavioural biases have been observed previously in this game (Dyson, 2019), and are in line with other work that suggests people are not able to consciously generate random actions (Figurska et al., 2008; Issartel et al., 2007; Neuringer, 1986; Treisman & Faulkner, 1987).

Importantly, EEG hyperscanning data revealed that the brain of the players encoded information about their own current and previous responses, as well as those of their opponents from the previous trials, with information related to previous trials only being encoded in the overall match losers. These results show that we can track the decision-related information in neural data. In determining their response on the current game, participants likely rely on what their opponent played, and to a lesser extent, what they themselves played in the previous game. While decoding results split by overall match winners and losers showed no differences in brain coding of decision-related information, we did find a different signature of decoding results between the two groups. Small differences in wins and losses in some pairs suggest that chance, not strategy, determined the winner, likely adding noise and obscuring potential group differences. Specifically, we found that whereas we could track the decision-making on the current trial for both the winners and losers, only the overall match losers encoded information about what they played themselves and what the other player chose on the previous trial. This suggests that losers likely incorporated information about the previous game, whereas this was not the case for the overall match winners. This reliance on previous responses, both of self and other, might hinder these participants, as the best strategy is to be as random, and therefore unpredictable, as possible (Glover & Dixon, 2017; West & Lebiere, 2001; Zhou, 2016).

Previous work on the Rock-Paper-Scissors game has used fNIRS to investigate prediction-related processes (Kayhan et al., 2022; Zhang et al., 2024). Although the results showed increased interbrain synchrony during the interactive task compared to playing the game alone, this measure did not increase when making explicit predictions (Kayhan et al., 2022). Previous work has also found increased interbrain synchrony in various regions when playing the game compared to rest (Kayhan et al., 2022; Zhang et al., 2024), but these findings could be driven by shared response-related processes (Burgess, 2013; Holroyd, 2022; Varlet & Grootswagers, 2024). In a recent study, Varlet and Grootswagers (2024) showed that interbrain synchrony measures are not sensitive to the information contained in the neural data. To address this, they introduced Interbrain RSA, a multivariate analysis method designed to assess the alignment of information across participants' neural signals. Building on this, we used decoding, a complementary multivariate approach (Grootswagers et al., 2017), to show that we can track the decision-related information about the responses of the participant and their opponent at different stages in the task. While the limited response options in our design precluded the use of Interbrain RSA, we show that decoding methods are highly effective in capturing decision-related neural information, highlighting the potential of this method for hyperscanning research as an extension of Interbrain RSA (Moerel et al., 2025; Varlet & Grootswagers, 2024). Unlike interbrain synchrony measures, which often rely on control conditions where participants are at rest or do not interact, the decoding method in this study leverages direct comparisons of neural activation associated with distinct response options. This makes decoding less susceptible to confounds such as shared visual or response-related information, offering a promising method to study neural processes underpinning real-time social interactions, in both cooperative and competitive settings, including in atypical populations (Charman, 2003; Coey et al., 2012; MacRitchie et al., 2017; Moreau et al., 2024; Raffard et al., 2015; Sebanz et al., 2006; Varlet et al., 2014; Zhang et al., 2024).

In conclusion, multivariate pattern analyses of EEG hyperscanning data enabled us to reveal how the human brain encodes self-other decision-related information over time during a competitive Rock-Paper-Scissors game. Despite the optimal strategy being randomness, players displayed critical behavioural biases and predictable strategies. EEG data showed neural encoding of current decisions, with overall match losers uniquely relying on past trials, potentially hindering performance. These findings highlight the challenge of overcoming cognitive biases and memory of prior outcomes for effective decision-making during competitive social interaction.

4. METHODS

4.1. Participants

Sixty-eight participants, grouped into 34 pairs, took part in the EEG study at Western Sydney University. Three EEG datasets were excluded from the analysis: two datasets had an issue with CMS which resulted in no EEG data for one of the players, and another dataset did not contain triggers. The sample included in this dataset consisted of 31 pairs (62 participants). Participants in this sample were 38 females / 22 males / 2 non-binary, 55 right-handed / 6 left-handed / 1 ambidextrous, mean age 27.85 years, SD = 6.73 years, range 18 – 47 years. All participants reported normal or corrected-to-normal vision. The EEG session took approximately 2 hours in total to complete and participants received a payment of $60 AUD. The study was approved by the Human Ethics Committee of the University of Western Sydney, and all participants provided written informed consent (H13092).

4.2. Stimuli and experiment

During the experiment, the two participants in each pair played a computerised version of the competitive Rock-Paper-Scissors game. Participants were seated behind a computer screen in separate rooms. In each game, both players choose between Rock, Paper, or Scissors. The outcome of the game is determined by three rules (Figure 1B): Rock beats Scissors, Scissors beat Paper, and Paper beats Rock. If both players choose the same response, the game is a tie. For each player, wins, losses, or draws therefore have equal probability.

An overview of the experiment is shown in Figure 1C. Each game consisted of three phases: Decision (2 s), Response (2 s) and Feedback (1 s), allowing us to assess decision-related information in the EEG signal at each stage without interference from future stages (Moerel et al., 2024). The Decision screen consisted of a central fixation cross and a prompt to “Make a decision”. During this phase, the participants could decide which response to select. During the Response phase, participants saw a prompt to “Select your response”, and the three options were displayed as a cartoon of the hand shapes associated with the game (Figure 1A); Rock was displayed as a fist, Paper as an open hand, and Scissors as a fist with the index and middle fingers extended, forming a V. The order of the Rock, Paper and Scissors images was chosen at random for each participant and each block but stayed the same for all games within a block. During this phase, participants used a 3-button box to select their response. The order of the three stimuli on the screen indicated the mapping between the buttons and responses, and therefore changed between blocks. This means that taking together the data from the whole experiment, the EEG signal was minimally contaminated by motor preparation and/or execution signals. The Response screen automatically timed out after 2 s, even if no response was given by one or both of the participants. The Response phase was followed by the Feedback phase, where the outcome of the game was displayed for 1 s. Participants saw the response of player 1 on the left of the screen, and the response of player 2 on the right of the screen. If no response was given, “No Response” was displayed. The outcome was displayed above the response images, as “Player 1 wins”, “Player 2 wins”, or “Draw”. If one of the participants did not respond, the other participant won the game.

The experiment consisted of 480 games of Rock-Paper-Scissors, divided into 12 blocks of 40 games, and took approximately 45 minutes to complete. The experiment was displayed on a mid-grey background using a VIEWPixx monitor at 120 Hz, using custom C++ code. Participants were seated approximately 60 cm from the screen. The images were displayed at 324 by 324 pixels (approximate 8.20 by 8.20 degrees of visual angle) and the fixation cross was 54 by 54 pixels (approximate 1.37 by 1.37 degrees of visual angle).

4.3. EEG acquisition and pre-processing

We collected continuous EEG data from 64 channels, digitised at a sampling rate of 2048 Hz, using the BioSemi Active-Two electrode system (BioSemi, Amsterdam, The Netherlands). Electrode placement followed the international 10-20 system (Oostenveld & Praamstra, 2001). The dataset consists of the raw EEG data as well as pre-processed data. We applied the following pre-processing steps, using the FieldTrip toolbox in MATLAB (Oostenveld et al., 2011). First, we epoched the data from 0.2 s before the onset of the Decision screen to 5 s after the onset of the Decision screen. The onset of each trial, in seconds as well as samples, can be found in the events.tsv file. Noisy channels, as identified through visual inspection, can also be found in the participants.tsv file. We interpolated noisy channels based neighbouring channels. Finally, we down-sampled the data to 256 Hz.

4.4. Behavioural analysis

To examine the behavioural responses recorded during the EEG session, we performed the following analyses. To assess the difference in performance between winners and losers, we obtained the distribution of game outcomes across pairs, categorising results as wins for the overall match winner, wins for the overall match loser, or ties. We examined the response bias by analysing how frequently the most, mid, and least chosen responses were played. To explore this further, we looked at the proportion of Rock, Paper, and Scissors responses separately for the most, mid, and least chosen responses. Additionally, we assessed the distribution of response changes between consecutive responses, split by the outcome of the previous game. Finally, we used a Markov chain model (Norris, 1998) with varying window sizes (5 to 100 previous games, in steps of 1) to predict each player's most likely response. We then calculated the prediction accuracy as a measure of response predictability for each participant. Together, these analyses provide insight into the strategies, response biases, and predictability of the participants.

4.5. Decoding analysis

We used a time-varying brain decoding analysis (Grootswagers et al., 2017) implemented using the CoSMoMVPA toolbox (Oosterhof et al., 2016) where we segmented each EEG epoch into three separate epochs, locked to the onset of the Decision screen (-200 ms – 2000 ms), Response screen (-200 ms – 2000 ms), and Feedback screen (-200 ms – 1000 ms) respectively. We applied baseline corrections for each separate epoch, using the window from -200 m to 0 ms, locked to the screen onset. We then averaged the resulting data into 250 ms time bins, resulting in a total of 20 time bins for the 0 to 5000 ms time-course. We then used a linear discriminant analysis classifier to determine if there was information about 1) the response made by the player, 2) the response made by the other player, 3) the player's response in the prior trial, and 4) the response of the other player in the prior trial. We did this separately for each 250 ms time bin and each participant using a 10-fold cross validation. Before decoding, we removed no-response trials and made 20 pseudo trials for each fold and response (Rock, Paper, or Scissors) by averaging 4 trials of the same fold and response to enhance the signal to noise ratio (Grootswagers et al., 2017; Scrivener et al., 2023). We calculated the accuracy separately for each of the 3 possible responses, and then averaged these measures to obtain the decoding accuracy for each timepoint. 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.

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