The Effect of Individual Coordination Ability on Cognitive-Load in Tacit Coordination Games

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Abstract. Tacit coordination games are coordination games in which communication between the players is not allowed or not possible. Some players manage to reason about the selections made by the co-player while others fail to do so and might turn to rely on guessing. The aim of this study is to examine whether good coordinators are associated with a higher or lower cognitive load relative to weaker coordinators. We aimed to answer this question by using an electrophysiological marker of cognitive load, i.e., Theta/Beta Ratio. Results show that good coordinators are associated with a higher cognitive load with respect to weaker coordinators.

Keywords: Tacit coordination games · EEG · Theta/Beta Ratio

1 Introduction

In this study we have applied a dual process account to human decision making in the context of a pure coordination game. In pure coordination games both players share common interests, and each player has an equal interest to successfully coordinate with the other player since coordinating on the same solution is beneficial for both [1].

Dual process cognitive framework posits that an interaction exists between intuitive automatic processes and more deliberate processes which are more controlled and reflective [2]. These two processes (intuitive and deliberate) are assumed to be involved in effective coordination [2] which requires reliance on common knowledge [3].

From the perspective of a dual process account, good coordinators might rely on a certain strategy [4–6] that may ease the coordination process and therefore reduce the associated cognitive load. Thus, the convergence on the same solution to achieve coordination might be entirely intuitive, involve heuristic choice strategies [7] and may therefore be regarded as a highly automatic process [8]. On the other hand, it might be that deliberate coordination relies on more cognitive resources and therefore entails a higher cognitive load when coordination is performed.

Thus, good coordinators manage to reason about the selections made by the co-player while weak coordinators fail to do so and might turn to rely on guessing. In tacit coordination games, the pure coordination game used here, players reach an agreement

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regarding a salient solution (i.e. a focal point) without any communication, (e.g. [1, 14, 20, 22]) considering only pay-irrelevant cues [9] such as spatial location. Therefore, tacit coordination games provide an excellent experimental environment for testing cooperative decision making in the context of dual process theory, since it is the most basic form of coordination and does not include any form of communication or conflicts of interest [9].

In this study we aimed to test whether there is a difference in cognitive load between good and poor coordinators in the context of a tacit coordination game by using an electrophysiological marker of cognitive load, i.e., Theta/Beta Ratio (TBR) [10–12]. TBR is known to decrease as cognitive load increases and vice-versa. Hence, in this study we utilize the TBR to find out whether good coordinators are associated with a lower TBR with respect to weaker coordinators.

2 Materials and Methods

The EEG Data acquisition process during the tacit coordination game session was recorded by a 16-channel g.USBAMP biosignal amplifier (g.tec, Austria) at a sampling frequency of 512 Hz. 16 active electrodes were used for collecting EEG signals from the scalp based on the international 10–20 system. Recording was done by the OpenVibe [13] recording software. Impedance of all electrodes was kept below the threshold of 5K [ohm] during all recording sessions.

In this study players were presented with a tacit coordination task in which they had to select a word from a given set of four words (in Hebrew) in order to coordinate with an unknown co-player [14]. This task consists of 12 different instances each with a different set of words. For example game board #1 displayed in Fig. 1 (B) contains the set (“Water”, “Beer”, “Wine”, “Whisky”). All the words belong to the same semantic category, however, there is at least one word that stands out from the rest of the set because it is different in some prominent feature, e.g., in the current example, a non-alcoholic beverage (“water”) which stands out among other alcoholic beverages. The more salient is the outlier, the easier it is to converge on the same focal point [15, 16].

![Game Boards](image)

Fig. 1. (A) Stand by screen (B) Game board #1 [“Water”, “Beer”, “Wine”, “Whisky”]

Figure 2 portrays the outline of the experiment. The list of four words were embedded within a sequence of standby screens each presented for $U(2,2.5)$ sec. The slide
presenting the list of words was presented for a maximal duration of 8 s and the next slide appeared following a button press. The order of the 12 games was randomized in each session. In each of the games the players were told that they have to coordinate with an unknown randomly selected co-player by choosing the same word from the given set of words. Participants were further informed that they will receive an amount of 100 points each in case of successful coordination and that otherwise they will get nothing. The participants were 10 students from Ariel University that were enrolled in one of the courses on campus (right-handed, mean age = 26, SD = 4).

![Fig. 2. Experimental paradigm with timeline](image)

In this study the following measures were computed.

**Individual Coordination Ability (ICA)** – The ICA measure reflects the individual coordination ability of each player with respect to the other players in the group [5, 6, 17]. The ICA calculates the total number of games in which each player was able to coordinate their responses against the entire population. The ICA is formally defined as follows:

\[
iCA(i) = \sum_{j=1}^{N} \sum_{k=1}^{t} \frac{CF(i, j, k)}{(N - 1) \times t}
\]

Where \( i \) denote the \( i \)th participant, \( j \) denotes the index of the \( j \)th co-player, \( N \) denotes the total number of participants, and \( t \) denotes the number of games in the experiments. The CF (coordination function) is defined as follows:

\[
CF(i, j, k) = \begin{cases} 
1; & \text{if players } i \text{ and } j \text{ chose the same label in game } k \\
0; & \text{otherwise}
\end{cases}
\]

The higher the player’s ICA value (ranged in [0, 1]), the higher the coordination ability.

**Theta Beta Ratio (TBR)** – is known from the literature to reflect cognitive load in various cognitive tasks and to covary with activity in the executive control and default mode networks [10, 12]. It was shown that the smaller the TBR, the cognitive load is higher [10, 12] (see Sect. 3 for more details).

3 EEG Metrics for Assessing Cognitive Load

Cognitive load refers to the amount of working memory resources required to perform a particular task [18] and there are two basic approaches for estimating cognitive load.
from EEG data. The first approach relies on power spectrum analysis of continuous EEG that reveals the distribution of signal power over frequency. In this method the EEG signal is divided into different frequency bands (i.e. delta, theta, alpha, and beta) in order to detect the bands sensitive to variations in load as a function of task demands. To estimate cognitive load, power-based features are extracted such as the signal’s average or maximum power, and the ratio between bands may also be calculated (e.g. [19–22]) as was done in the current study (i.e. the energy ratio between the theta and beta bands, the TBR measure, was computed). Power spectrum analysis was used in various studies associated with the information systems (IS) discipline [27].

The second approach involves measuring the neural signal complexity that has been associated with both memory ability [23] and cognitive load [21]. Common methods in this category include fractal dimension (e.g. [24]), multi-scale entropy (e.g. [25]), and detrended fluctuation analysis [26, 27]. Table 1 summarizes the above-mentioned EEG metrics.

<table>
<thead>
<tr>
<th>Cognitive load estimation technique</th>
<th>Metric 1</th>
<th>Metric 2</th>
<th>Metric 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power spectrum analysis</td>
<td>Accumulated band power ratio (e.g. accumulated TBR)</td>
<td>Maximal band power ratio (e.g. maximal TBR)</td>
<td>Average band power ratio (e.g. mean TBR)</td>
</tr>
<tr>
<td>Neural signal complexity</td>
<td>Fractal dimension</td>
<td>Multi-scale entropy</td>
<td>Detrended fluctuation analysis</td>
</tr>
</tbody>
</table>

Xie and Salveny [28, 29] have differentiated between several main indices meant to quantify mental workload. These measures include instantaneous load (dynamic changes in load during task performance), peak load, average load, overall load and accumulated load. In the current study we have created a hybrid index as follows. For each epoch we have first calculated the accumulated cognitive load [12], by calculating the energy ratio between theta and beta bands for each participant on each single epoch. Then, we have averaged the ratio across all epochs of an individual player to obtain the average cognitive load.

4 Data Processing and Analysis

Based on the literature (e.g. [11, 30–32]), we focused on the following cluster of frontal and prefrontal electrodes (Fp1, F7, Fp2, F8, F3, and F4). The preprocessing pipeline (see Fig. 3) consisted of band-pass filtering [1, 32] Hz. Subsequent by notch filtering of [50] Hz for an artifact removal following iCA. The preprocessing pipeline (see Fig. 3) consisted of band-pass filtering [1, 32] Hz an artifact removal following iCA. The data was re-referenced to the average reference and down sampled to 64 Hz following baseline correction. Data was analyzed on a 1-s epoch window from the onset of each game.
To calculate the energy in the Theta and Beta bands, for each epoch, we have used the Discrete Wavelet Transform (DWT) [33, 34]. The DWT is based on a multiscale feature representation. Every scale represents a unique thickness of the EEG signal [35]. Each filtering step contains two digital filters, a high pass filter, \( g(n) \), and a low pass filter \( h(n) \). After each filter, a downsampler with factor 2 is used in order to adjust time resolution. In our case, we used a 3-level DWT, with the input signal having a sampling rate of 64 Hz. As can be seen in Fig. 4, this specific DWT scheme resulted in the coefficients of the four EEG main frequency bands (see red rectangles in Fig. 4).

To calculate the cognitive load, which is expressed by the TBR, the DWT was applied on all the epochs to calculate the TBR. That is the ratio of the average energy in each one of the Theta and Beta bands (Theta/Beta) was calculated in each of the epochs.

To find out whether there is a direct and significant relationship between each player’s individual coordination ability (iCA) and the cognitive load (TBR) we performed several computations. First, we calculated the iCA value of each player. Next, the average individual TBR was calculated for each of the six channels by weighting the 12 epochs. Finally, for each channel, the relationship was calculated between the mean individual TBR and the iCA using linear regression (Table 2).
Table 2. Results of modeling the relationship between ICA$^*$ and TBR

<table>
<thead>
<tr>
<th>Channel</th>
<th>Regression model</th>
<th>p-value</th>
<th>R-squared</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 - Fp1</td>
<td>TBR = 18.415 - 46.802$^*$ICCA</td>
<td>0.0147</td>
<td>0.5456</td>
</tr>
<tr>
<td>2 - F7</td>
<td>TBR = 17.886 - 45.396$^*$ICCA</td>
<td>0.0240</td>
<td>0.4901</td>
</tr>
<tr>
<td>5 - Fp2</td>
<td>TBR = 18.401 - 46.191$^*$ICCA</td>
<td>0.0251</td>
<td>0.4859</td>
</tr>
<tr>
<td>6 - F8</td>
<td>TBR = 18.200 - 44.376$^*$ICCA</td>
<td>0.0235</td>
<td>0.4934</td>
</tr>
<tr>
<td>9 - F3</td>
<td>TBR = 19.660 - 50.880$^*$ICCA</td>
<td>0.0475</td>
<td>0.4062</td>
</tr>
<tr>
<td>13 - F4</td>
<td>TBR = 19.785 - 50.793$^*$ICCA</td>
<td>0.0068</td>
<td>0.6207</td>
</tr>
</tbody>
</table>

(* in this table ICA denotes individual coordination ability)

Table 2 presents the regression model for each of the six channels. It can be seen that all regression lines turned out to be significant (p < 0.05). The highest coefficients in the regression model were obtained for F3 and F4, while the most significant p-value was obtained for F4. The negative coefficient denotes that there is a negative relationship between iCA and TBR. That is, the higher is the iCA, the smaller is the TBR. Hence, higher iCA is associated with a higher cognitive load. Figure 5 presents the regression line for the F4 channel. The regression line shows a clear negative relationship between iCA and TBR.

![Fig. 5. The regression model of F4](image)

5 Conclusions and Future Work

To the best of our knowledge, this is the first time in which a correlation is shown between individual coordination ability in tacit coordination games and electrophysiological marker of cognitive load. Specifically, we have demonstrated this relationship
by using a prefrontal and frontal cluster of electrodes. This result corroborates previous research showing that complex cognitive tasks depend on prefrontal [11] and frontal [12] cortex activation. This result also strengthens the connections found between TBR fluctuations and executive control [11]. It might have been hypothesized that better coordinators lean on a certain behavioral strategy, and in turn utilize less cognitive resources than weaker coordinators. However, our results do not coincide with this assumption but rather demonstrate the opposite, namely that better coordinators use more cognitive resources in order to coordinate. Hence, our results also support the dual process theory as was utilized by Tversky and Kahneman to discuss human bounded rationality [36].

It appears that in order to coordinate, players rely on deliberation (System-2) mode of thinking which is more deliberate and analytical than intuition (System-1) which relies on fast heuristics and is therefore more automatic.

Apparently, the results of this study stand in contrast to previous findings showing significant negative correlations between glucose consumption and task performance [37–39]. These studies indicate that good performers of a complex task may use less brain circuits or less inefficient brain areas compared to poor performers and underscore the effects of practice. These results are also in agreement with behavioral findings showing that experts perform more efficiently than novices in decision-making contexts [40–42]. Taken together with the glucose metabolism studies, it may very well be the case that more efficient performers, as a result of expertise and practice, rely more efficiently on cognitive resources. However, in our study better coordinators may be associated with a higher cognitive load, not because of less efficiency in the functionality of brain circuits, but rather because they reason more deliberately (a system 2 process) about the selections made by the other co-player to reach successful coordination.

There are many avenues for future research. For example, previous studies have shown that culture [6, 43] and social value orientation [44] affect human behavior in tacit coordination games. It will be interesting to see if the TBR is also correlated with the abovementioned measures. Also, it will be interesting to observe fluctuations in TBR as a function of varying levels of difficulty and complexity of other tacit coordination games.

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References