The Relationship Between Mental Effort and Social Value Orientation in Resource Allocation Problems

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Abstract Resource allocation tasks are a central focus of game theory, where a player must allocate a limited set of resources among himself and others. Resource allocation tasks in game theory provide a framework for analyzing strategic decision-making in various economic, political, and social contexts. The Social Value Orientation (SVO) index is a concept used in social psychology to describe the degree to which individuals prioritize their interests over the interests of others in social dilemmas. In resource allocation tasks, the SVO may be used as an indicator to evaluate player's behavior. In this study, an experimental set-up was built to examine the relationship between the player's SVO index and his mental effort, which is measured by evaluating the Theta to Alpha ratio based on an EEG measurement. The results show a significant linear relationship between the player's SVO value and its mental effort. That is, the smaller the SVO value (a more competitive player), the greater the mental effort he invests in the resource allocation task.

Keywords EEG · Theta/Alpha Ratio · Social Value Orientation · Resource Allocation

1 Introduction

In game theory, resource allocation tasks (e.g. [1, 2]) refer to situations where a player must allocate a limited set of resources among himself and others. These resources can range from physical commodities like money to intangible assets like

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F. D. Davis et al. (eds.), *Information Systems and Neuroscience*, Lecture Notes in Information Systems and Organisation 68,
https://doi.org/10.1007/978-3-031-58396-4_17

time or attention. The goal of each player is typically to maximize its own utility [3], which can be defined in several different ways depending on the game being played. Resource allocation tasks exists in many forms in the game theory literature: ranging from simple two-player games like the ultimatum game [4], where one player proposes a division of resources and the other player can either accept or reject the offer, to more complex games involving many players and multiple rounds of play (e.g. [5]). In some cases, the allocation of resources may be fixed, and players must compete to see who can claim the most valuable share of the resources. In other cases, players may be able to negotiate with one another to divide the resources in a mutually beneficial way [6].

One way to evaluate players' utility function via the Social Value Orientation (SVO) index [7, 8]. SVO is a concept used in social psychology to describe the degree to which individuals prioritize their interests over the interests of others in social dilemmas. SVO can be thought of as a continuum, with individuals at one end exhibiting a "prosocial" orientation, in which they prioritize the collective good and seek to maximize the benefits to all parties involved, while individuals at the other end exhibit a more "individualistic" orientation, in which they prioritize their self-interest and seek to maximize their gains, even at the expense of others. Individuals with a more prosocial SVO tend to exhibit greater trust, cooperation, and altruism. In comparison, those with a more individualistic SVO tend to exhibit greater competition and selfishness. Today, the most reliable way to measure the SVO value is through the "slider" questionnaire [7], which includes six questions about resource distribution. The result of the questionnaire is a number on a continuous scale that describes the player's preferences, where an SVO value of 0 represents an individualist player, and a value of 45 represents a prosocial player.

Previous research has shown that the Theta to Alpha Ratio (TAR) brainwaves is a good estimator of mental effort (e.g. [9, 10]), or the level of cognitive resources an individual is expending in a given task. Theta waves are associated with low-frequency brain activity that is typically observed during states of relaxation, daydreaming, or light sleep. In contrast, alpha waves are associated with higher-frequency brain activity typically observed during wakeful mental effort. Overall, the ratio of theta to alpha waves provides a valuable measure of mental effort, reflecting the underlying neural processes associated with cognitive engagement and attention. A high TAR value indicates low mental effort, and a low value indicates high mental effort. Following a previous study [11] which showed that there is a difference in the distribution of the TAR values for binary prosocial or individualistic labels, in this study, we would like to check whether there is a significant relationship between the *continuous SVO index* and the distribution of the TAR values. Our assumption in this study, following the results of previous studies (e.g. [2, 11, 12]), is that by using the SVO slider index [7], which is an extension of the SVO ring [13] index which generates a continuous SVO index (i.e., SVO angle) instead of a categorical index (i.e., prosocial or individualistic), we will be able to show a significant linear or polynomial relationship to electrophysiological indices.

2 Experimental Design

The study comprised the following stages. First, participants received an explanation regarding the overarching aim of the study and were given instructions regarding the experimental procedure and the interface of the application. Next, we have measured the SVO of the player using the "slider" method [7] and categorized it as "prosocial" or "individualistic". Then, each player was presented 18 resource allocation questions. Each such question included two resource-sharing options which should be divided between himself and another participant unknown in the experiment (Fig. 1 shows the resource allocation application screen). The number of points presented at the upper part of the screen is for the main player and the number of points at the lower part is for the other player. The player must choose within 8 s otherwise this will get no points. The position of the options on the screen was randomized. One option was the prosocial option (maximizing the joint profit of the two players), and the other an individualistic option (maximizing the personal profit of the player). Between the games a stand-by screen appeared for 1 s.

The participants were 10 students from the university that were enrolled in one of the courses on campus (right-handed, mean age = ~25, SD = 3). The EEG Data was recorded by a 16-channel g.USBAMP bio signal amplifier (g.tec, Austria) at a sampling frequency of 512 Hz, with 16 active electrodes based on the international 10–20 system. Recording was done by the OpenVibe [14] recording software. Impedance of all electrodes was kept below the threshold of 5 K [ohm] during all recording sessions.

We assessed the mental effort in each epoch using the Theta/Alpha ratio (TAR). The TAR measure of mental effort is based on the hypothesis that an increase in workload is associated with an increase in theta power with a simultaneous decrease in alpha power (e.g. [9, 15]). In terms of topographic distribution, previous studies have shown that workload decreased alpha power at parietal regions and increased theta power at frontal regions (e.g. [16]). Hence, in this study we have focused on the analysis of the of frontal and prefrontal cluster electrodes (Fp1, F7, Fp2, F8, F3, and F4). For each epoch we have calculated the accumulated mental effort [17], by

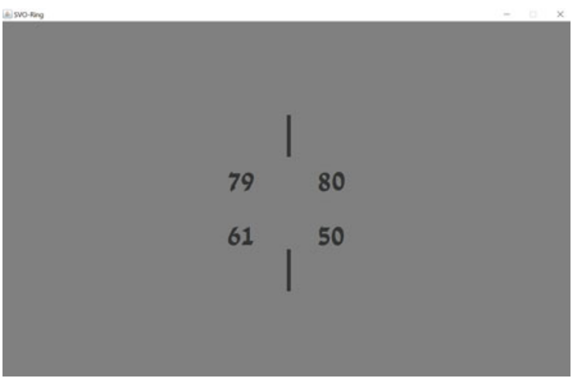

Fig. 1 Resource allocation application screen

calculating the energy ratio between theta and alpha bands for each participant on each single epoch.

3 Data Processing and Analysis

To improve the signal-to-noise ratio and reduce the effect of artifacts created during the EEG recording (e.g., eye movements, muscle activity, and electrical interference) before extracting the TAR value we have implemented data preprocessing pipeline, as was done in previous studies (e.g. [2, 10, 11]). The pipeline used a combined filter (band pass combined with a notch filter) followed by a re-reference scheme to an average reference, and decomposed using independent component analysis (ICA) [18]. To end the process the EEG signal than down sampled to 64 Hz following a baseline correction. Data was analyzed on a 1-s epoch window from the onset of each game.

Next, we estimated the intensity of the cognitive workload in each epoch using the TAR index. First, we have calculated the energy in the Theta and Alpha bands by using the Discrete Wavelet Transform (DWT) [19]. The DWT divides a signal into multiple frequency bands, each representing a different level of detail or approximation. This allows for a more efficient representation of the signal compared to other transforms, such as the Fourier transform, which represent a signal in terms of its frequency components only [19]. In this research, we used a 3-level DWT, which can extract the theta and alpha band (e.g. [2]) which are required to calculate the TAR index. The output of the DWT (i.e., the power of theta and alpha bands) is a signal which variant over the epoch time. To calculate the TAR for the entire segment we averaged the power of the whole epoch, (Eq. 1), and divided them to calculate the TAR index of the current epoch.

$$P_x = \frac{1}{T}\sum_{t=1}^{T} x^2(t) \tag{1}$$

We analyzed the distribution of 180 TAR values (18 epochs per player of 10 different players) that were extracted from the EEG segments according to their corresponding SVO value. We used a one-dimensional linear regression model to verify whether there is a relationship between the two variables, SVO and TAR, which represent a mental effort in resource allocation problems. The regression model showed that SVO significantly predicted TAR in resource allocation games. SVO also explained a significant proportion of variance in depression scores, $R^2 = 0.68716$, $p < 0.05$. Visualization of the average TAR values of each player according to his corresponding SVO index alongside the regression is presented in Fig. 2.

The TAR ratio represents the mental workload that the player invests during the task. The greater the workload the higher the TAR index should be (simultaneous change in two indices—decreased alpha and increased theta). These results,

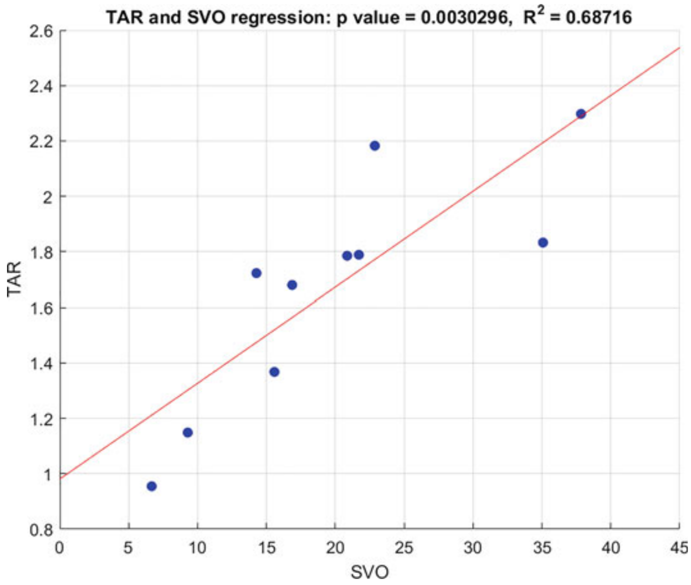

Fig. 2 TAR as function of SVO profiles

which are based on electrophysiological measurements, show that humans who are more prosocial according to the SVO theory (i.e., higher SVO index) invest a larger cognitive workload than their individualistic counterparts.

4 Conclusions and Future Work

This research presents for the first time the significant and positive relationship between the TAR, which is an electrophysiological marker of mental effort, and SVO in the context of resource allocation tasks. Specifically, this finding was demonstrated with the use of a prefrontal and frontal cluster of electrodes. This result corroborates previous research showing that SVO profiles may affect the strategic behavior of players [12], and that different behavioral strategies and indices may be accompanied by electrophysiological changes (e.g. [16, 20]). Following the results obtained in this study, there are many avenues for future research. First, it will be possible to examine the effect of the structure of the questionnaire, such as the absolute number of resources or the difference between the various options, on the distribution of electrophysiological indices or on the activity of specific regions in the brain. Second, according to [21] mental work load also affected parietal brain areas. It will be interesting to explore the effect of these areas on the TAR distribution and the correlation to the prefrontal and frontal areas. Third, it would be interesting to examine the distribution of electrophysiological results depending on the demographics and gender of the subject. Finally, previous studies have shown that other measures such culture [22, 23] and loss-aversion [24] may affect human behavior in decision making scenarios. It will be interesting to see if the TAR is also correlated with the abovementioned measures.

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