Title: Brain Mapping of Behavior Contagion Based on Visibility Graph Analysis of ERP Signals

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Abstract

Behavior contagion in social decision-making refers to the alignment of an individual's behavior and decisions with those of others in social interactions. Despite the previous studies in the field, it is still required to be well understood that how the brain activities are spatio-temporally organized while contagion is occurred. Since brain activities include both positive and negative fluctuations, monitoring of these occurrences in a polar space using visibility graph can aid in a better understanding of this phenomenon. Therefore, we exposed a healthy group to a psycho-economic task while their EEG was simultaneously recorded. The participants performances were compared before and after observation of others' preferences in a dictator game task. Subsequently, two groups were differentiated based on their behavior contagion rate. Then, visibility graph of event related potentials in both contagion and non-contagion groups were compared before and after observation. Our results indicated that the visibility graph features differentially change in various EEG channels. For instance, changes in clustering coefficient, modularity, and efficiency of VGs indicated that number of ERP components varies after contagion specifically at the frontal, frontocentral, centroparietal and parietal regions. This may put a question mark on ERP analysis of contagion while using the same number and length of components (eg. P300) for comparison of ERPs before and after contagion.

Keywords: Behavioral contagion, social decision making, dictator game, event-related potential (ERP), visibility graph

Introduction

Human social decision-making is influenced by several neurobehavioral mechanisms, including trust, social influence, observational learning, conformity, and behavioral contagion. These mechanisms have been extensively studied in social and cognitive neuroscience (Charpentier et al., 2020; Mahmoodi et al., 2022; Rilling & Sanfey, 2011; L. Zhang & Gläscher, 2020), often through a neuroeconomic approach that employs experimental designs derived from game theory (Lee, 2008; Ridderinkhof et al., 2004; Sanfey, 2007) . One particularly important phenomenon in social decision-making is behavioral contagion, which refers to how an individual's decisions are influenced by the choices of others (Suzuki et al., 2016; Thomas et al., 2022) . This contagion can manifest in both positive (e.g., altruistic or prosocial) and negative (e.g., risky or antisocial) behaviors, each governed by complex neurobehavioral processes(Dimant, 2019; Martínez et al., 2023; Suzuki et al., 2016; Tsvetkova & Macy, 2014). Such a phenomenon has been investigated using neuroimaging techniques like EEG and fMRI for instance, Suzuki et al showed the contagion of risky behaviors due to observing the risky behavior of others can be explained by a neurocomputational approach.In this regards, EEG based analysis has raised interest because of high temporal resolution .

Electrophysiological studies, particularly those utilizing Event-Related Potentials (ERPs), have traditionally been used to examine decision-making processes. These studies typically analyze ERP components based on two factors: amplitude and latency(Congedo, 2018; Donoghue & Voytek, 2022). one of the shortcomings and challenges in past ERP time series studies is the number of components and time windows of the components. These deficiencies could be covered by Visibility Graph (VG) analysis, as a promising method for understanding the nonlinear dynamics of neural time series data. Unlike conventional ERP analysis, VG maps time series data into a graph structure which enables us to identify hidden patterns within high-volume sequential data(Sannino et al., 2017; Sengupta et al., 2013; Sulaimany & Safahi, 2023; Zheng et al., 2021). Prior research suggests that behavioral contagion influences ERP time series(Deldoost et al., 2024), making it important to explore new analytical frameworks that can capture these dynamics more effectively. Considering the fact that ERP time series contain both positive and negative fluctuations, examining them in polar space through graph-based methods may provide deeper insights into contagion effects. Given its ability to model complex nonlinear phenomena, VG analysis presents a compelling alternative to traditional ERP assessment methods(Congedo, 2018).

In this study, we apply Visibility Graph analysis to ERPs associated with behavioral contagion in social decision-making. The VG approach(Zheng et al., 2021) is a strong abstraction of time series ERP data based on points of high-volume sequential data(Lacasa et al., 2008).Our primary objective is to examine the characteristics of the graph structures derived from ERP data in individuals who exhibit behavioral contagion. Specifically, we aim to determine whether neural indicators of behavior contagion can be identified through these graph-based features including clustering coefficient, local and global efficiency, pathlengths, modularity, and radius. To investigate this, we designed an experiment based on the Dictator Game, a well-established task in neuroeconomics and game theory, while simultaneously recording brain electrical activity.

By leveraging this novel methodological approach, our research seeks to advance the understanding of neural mechanisms underlying behavioral contagion and contribute to the development of new analytical techniques in cognitive neuroscience.

Methods

Participants

The study included 30 healthy participants aged between 20 to 30 years (mean age ۲۷±2.1), comprising 15 men and 15 women, who voluntarily entered the test based on public calls, and all were right-handed with no history of neurological or psychological disorders and were not on any medication. Among them, 2 participants were removed. Additionally, 6 dollars were allocated for one hour of testing. This research was approved by the ethics committee with the ethical code IR.UT.IRICSS.REC.1400.034, and all participants signed an informed consent form to participate in the experiment.

Stimuli and Procedure

The stages of the experiment were as follows: after a general description of the experiment and answering the participants' questions, they entered the main phase of the test following a trial run to ensure their learning. During a behavioral task ,modified dictator game, (It should be noted that various models of the dictator game have been used in research(Engel, 2011) , which may be interactive or non-interactive, meaning the dictator and recipient can switch roles (Grech & Nax, 2020). In this study, a non-interactive model was used, where the dictator does not receive feedback in the form of reward or punishment. Also, both anonymous and identified peer types are used in research (Rilling & Sanfey, 2011), The version we use is similar to the paper from fehr's group (Krajbich et al.,2015) and the paradigm similar to mobasseri et al.

As Heinrich and Weinmann .(2013) explain , In the classic dictator game introduced by Forsythe et al. (1994) (*Fairness in Simple Bargaining Experiments*, n.d.),the budget constraint has a slope of −1, reflecting the fact that each cent transferred to the recipient decreases the dictator's own earnings by the same amount. However, in altered versions of the game, this trade-off rate—represented by the slope of the budget line—can differ (Heinrich & Weimann, 2013))

an EEG recording was also conducted simultaneously. These experimental stages are conceptually illustrated in Figures 1. Overall, the behavioral experiment consisted of three phases including Phase 1: Involving the individual's own decisions, Phase 2: Involving the observation of others' decisions (first predicting someone else's choice and then observing), and Phase 3: Involving the individual's own decisions.

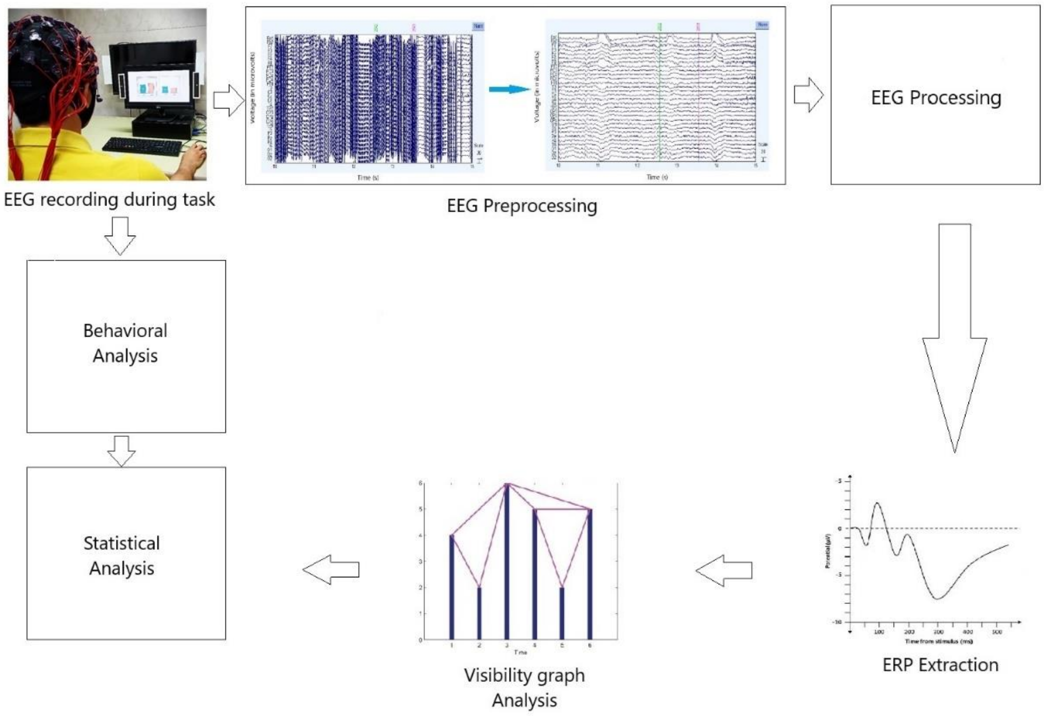

Figure ١. Experimental, procedure

General description of the experiment:

- Preparation and familiarization with the experiment:

First, explanations about the generalities of the experiment were provided, stating that the dictator game was explained to them and it was emphasized that there is no concept of right/wrong or good/bad choices, nor any winning/losing in this experiment to minimize potential effects of these factors. Then, the preparation of the EEG cap and device was done, and a trial was conducted to ensure the participant had learned the tasks.

- Leaving the laboratory and starting the recording:

To prevent social priming of the participant by the experimenter(Gilder & Heerey, 2018), after ensuring that the participant fully understood the experiment and was briefed, the experimenter visibly left the laboratory and discreetly monitored the participant to minimize the effect of the experimenter's presence on the participant's decision-making. To reduce stress, it was mentioned to them that they could call out loudly whenever needed for the experimenter to come (while no one felt the need to call out during this time).

- End of the experiment and answering potential questions from the participant:

At this stage, potential questions from the participant were answered, and in addition to monetary compensation, a certificate of appreciation was also awarded to them.

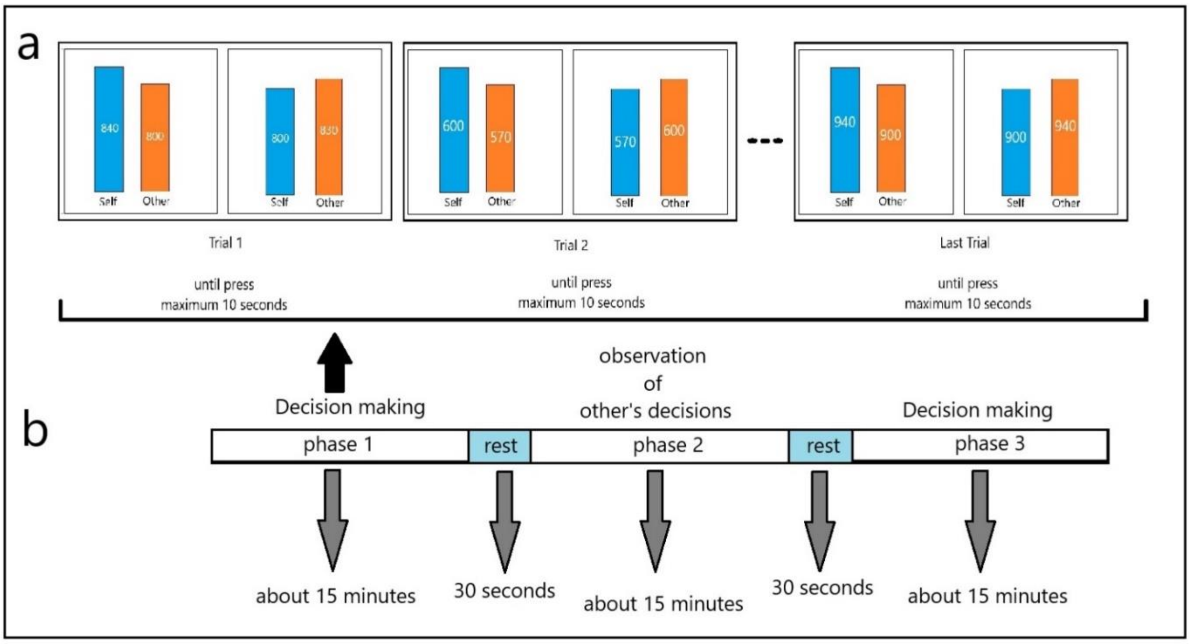

Figure4. overview of task paradigm.

a: during the task, participants must choose between left or right options in each changing trial. (the amount of self/other is more than other/self in each random trial). this part is repeated in all phases whereas phase 2 is the observational phase.b: in phases 1 and 3, subjects must select and make decisions, but in phase 2, subjects must observe others' decisions while they predict each of the other selections, The duration of each test phase was approximately 15 minutes and depended on the response time of the subjects.

Behavioural analysis

To observe the behavior contagion, based on similar studies (Suzuki et al., 2016), the differences between the decisions in the first and third phases of the experiment, that is, the differences between one's own decision-making before and after observing the decisions of others, were examined in such a way that the differences in trials in decision-making were calculated using MATLAB. Then, the participants were divided into two groups: contagion and no contagion, Based on recent studies to determine the threshold, Behavioural contagion rate was chosen (Mobasseri et al., n.d.),such that participants with a difference in the number of decisions in phases 1 and 3 greater than or equal to 6 were classified as the contagion group, while the remaining participants with a smaller difference were placed in the no contagion group.

EEG Recording and (Pre)processing

The data obtained from electroencephalography was recorded using a 64-channel gel-based device with a sampling rate of 1000 Hz. Data acquisition was performed with a monopolar setup, and the EEG cap was placed on the subjects' heads using the standard 10-20 method.

In the preprocessing stage of the data, motion artifacts, eye blink noise, eye movement noise, EMG noise, and ECG noise were removed using the ICA method. A bandpass filter from 0.1 to 30 Hz was also applied to the data, all of which was conducted using the MATLAB-based software EEGLAB, and the obtained data were subsequently analyzed using ERPLAB, considering 200 milliseconds before and 800 milliseconds after the stimulus

Data Analysis

Visibility graph

After obtaining the ERP time series, these time series were analyzed using the Visibility graph analysis approach, such that the ERP time series for each EEG channel were considered as inputs. After the calculations of the Visibility graph network analysis using Python with the NetworkX library, the values related to the visibility graph were separately calculated for each EEG channel for the first phase and the third phase of the experiment, The graph features included: Clustering Coefficient, pathlengths, global efficiency, local efficiency, modularity, and radius.

The visibility graph is defined [20] as below if and only if:

$$x_{m+i} < x_n + \frac{(n - m + i)}{n - m}(x_m - x_n) \qquad \forall i \in Z+ : i < n - m$$

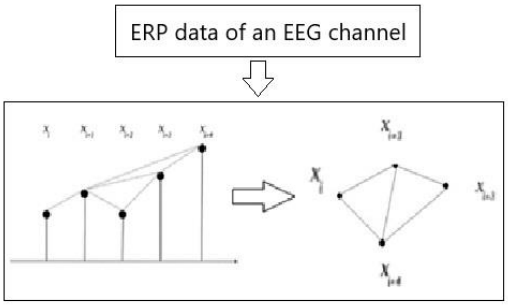

Figure ٢. schematic shape of visibility graph

Therefore, to implement the visibility graph on ERP time series:

$$x_i = ERP_{CHANNEL\ (i)}$$

$$f\text{(visibility graph)} = \begin{cases} 1 : & \boxed{x_{m+i} < x_n + \frac{(n - m + i)}{n - m}(x_m - x_n) \qquad \forall i \in Z+ : i < n - m} \\ 0 : & \text{else} \end{cases}$$

Statistical analysis

Behavioral data consisted of continuous integer types and visibility graph data included clustering coefficient, pathlength, global efficiency, local efficiency, of continuous decimal type, and modularity and radius of discrete type. After calculating the quantitative values of the graph features, the Kolmogorov-Smirnov test was used to check for normality, and then, considering the non-normal distribution of the data, the Wilcoxon Signed Rank statistical test was used to examine significance.

Finally, the family wise error (FWE) correction method with the Bonferroni-Hochberg approach was employed to determine the most significant components in each EEG channel for each graph feature to create the related maps and diagrams.

Subsequently, the relationship between behavioral changes and significant changes in the brain graph features in the first and third phases of the experiment will be calculated using Pearson correlation.

Results

Behavioral Result

The results of the behavioral data show that 13 individuals were placed in the contagion group and 15 individuals in the no contagion group, such that the individuals in the contagion group changed more than 6 decisions before and after second phase (observing other's behavior) .

The results of the behavioral analysis in the two groups, contagion and no contagion, are presented in Table 1.

Table 1. Demographic of the subjects with behavioral contagion scores

Contagion Group				NO Contagion Group			
Subject ID	Gender	Age	Behavioral Result	Subject ID	Gender	Age	Behavioral Result
1	Female	23	14	1	Male	30	1
2	Female	30	8	2	Female	20	-5
3	Male	25	8	3	Female	25	1
4	Male	23	8	4	Male	27	0
5	Female	26	8	5	Male	28	-1
6	Female	30	15	6	Male	28	1
7	Female	26	9	7	Female	25	3
8	Male	23	6	8	Female	24	0
9	Female	25	19	9	Male	29	1
10	Female	27	7	10	Male	30	-2
11	Male	30	11	11	Female	28	-5
12	Male	30	11	12	Male	27	2
13	Male	28	10	13	Female	25	3
14	Removed from list			14	Male	30	1
15	Removed from list			15	Female	25	1

After conducting the Wilcoxon statistical test in the first and third phases for the visibility features of the contagion group, significant channels with a significance level of p value<0.05 for each feature are presented in Table 2.

Table2. significant channels for visibility graph features in contagion group

Feature	Significant Channels with p value <0.05
Clustering Coefficient	Fpz, Fp2, AF3, AF4, F7, F5, F3, F1, FT7, FC5, FC3, FC1, FC6, C5, C3, C1, TP9, TP7, CP5, CP3, CP1, P7, P5, P3, P1, P2, PO3, POz, PO8, O1, Oz, O2
Pathlength	CP3
Global Efficiency	FC5,C5,C1,CP5,CP3,CP1,P5,P6
Local Efficiency	Fpz,Fp2,AF3,F7,F5,F3,F1,FC5,FC3,FC1,C5,TP9,TP7,CP5,CP3,P7,PO3,O2
Modularity	FC4,T7,PO3
Radius	PO3,PO8

The topoplots obtained from the averages and p values of each feature of the visibility graph are shown in Figure 5. These average topoplots are for Phase 1 and Phase 3 of the experiment, as well as for comparing Phase 1 and Phase 3 with p value.

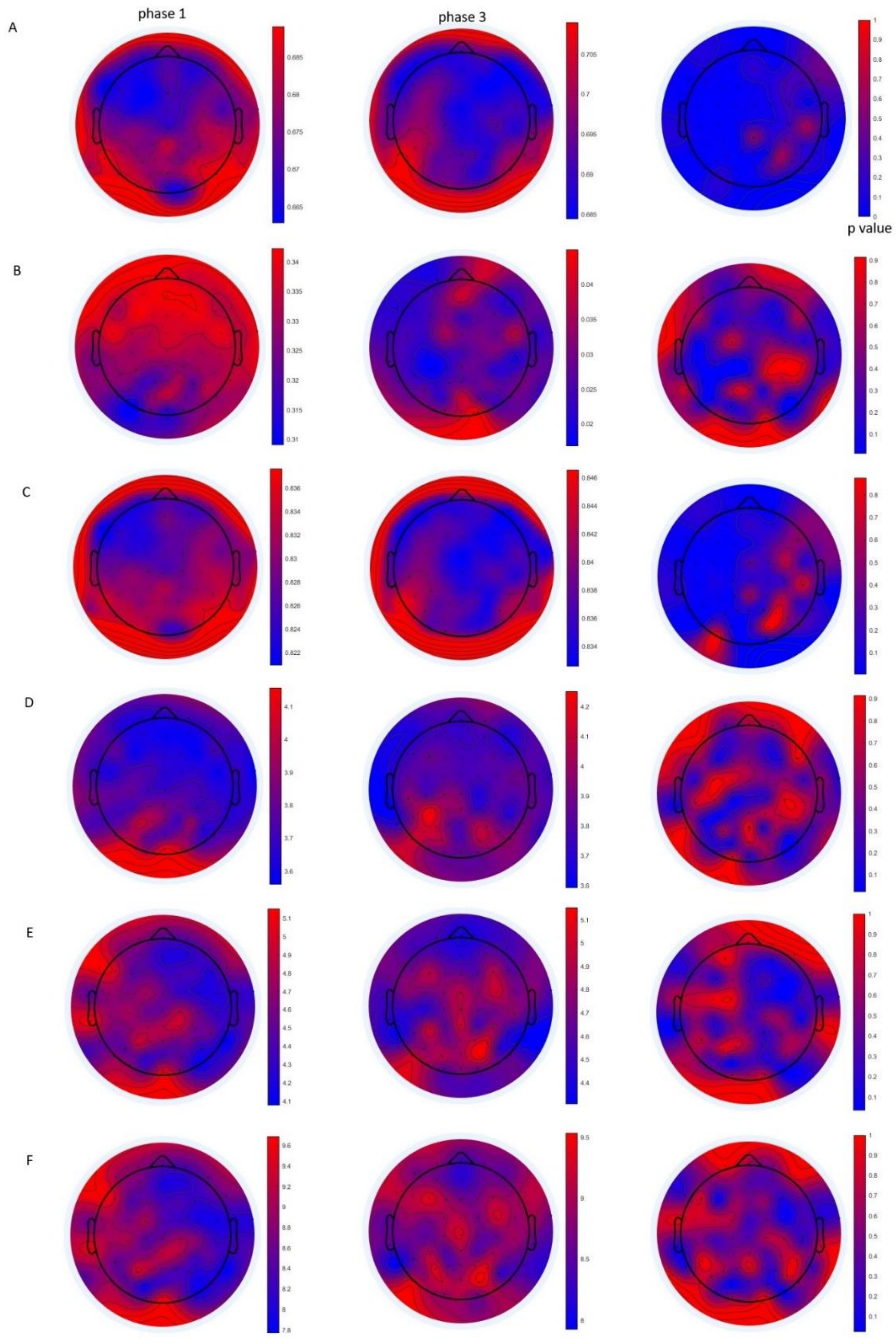

Figure 5. Topoplots of visibility graph features achieved from ERP signals: the first column indicates the average of features in phase 1, the second column indicates the average of features in phase 3, and the third column indicates the p value of differences between phase 3 and phase 1. A: clustering coefficient, B: global efficiency, C: local efficiency, D: pathlengths, E: radius, F: modularity

For the relationship between behavioral changes and changes in each of the graph features, the most significant EEG channel was calculated. According to Figure 6, regression lines with coefficients r and p were drawn, showing that the highest significant relationship was for radius (r=0.68۹, p=0.009) and modularity (r=0.58۶, p=0.035)

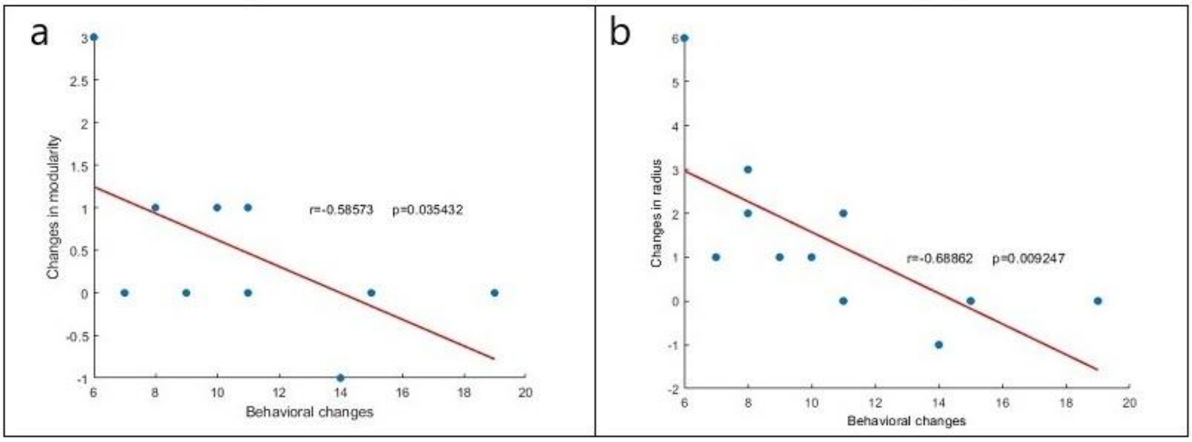

Figure 6. regression lines indicate relationships between behavioural changes and change in visibility graph features (a: changes modularity and behaviour in PO3, b: changes in radius and behaviour in PO3)

Discussion

In this research, we sought a model for the brain mechanism of behavioral contagion based on the visibility graph, as this type of modeling represents a novel approach for processing brain signals according to previous studies (Sulaimany & Safahi, 2023). Since the visibility graph transforms time series data into a graph, we used this nonlinear model to analyze ERP data, as the nature of these brain signals is inherently complex and nonlinear(Poikonen et al., 2023; K. Zhang & Hu, 2024). After conducting behavioral experiments and simultaneously recording EEG, we calculated the features of the visibility graph for the ERPs obtained from it. For the contagion group, the results are observable in a topoplot for the mean and also the significance levels of the comparison between phases 1 and 3 of the experiment. On the other hand, considering the most significant EEG channels in this contagion group, the results indicate that the obtained clustering coefficient feature in channel P7 is the most significant area of the brain for this feature. Additionally, for the obtained pathlengths feature, channel CP3 is the most significant, while for the obtained global efficiency feature, the most significant channel is also CP3. For the obtained local efficiency feature, the most significant channel is P7, and for the obtained modularity feature, the most significant channel is PO3. Furthermore, for the obtained radius feature, the most significant channel is also PO3.given that these areas were exclusively observed in the contagion group, it can be concluded that in behavior contagion, based on the results of clustering coefficient and local efficiency, individuals are more influenced by visual and spatial cues. Therefore, improving visual-spatial information processing should enhance sensitivity to the behavior of others, which is associated with increased social information processing through observing others. regarding the results of global efficiency and path lengths in the left centroparietal region, it is associated with better integration of sensory-motor and social information. Therefore, concerning the behavior contagion, it can be concluded that better coordination between observing the behaviors of others and decision-making for contagion is likely related. additionally, in the results of modularity in the PO3 region, it signifies more independent and modular processing of spatial social information. Thus, it can be concluded that regarding behavior contagion, there is more specialized processing of visual and social information in this area, with a greater focus on social cues, which may indicate a higher sensitivity to the behaviors of others that play an important role in behavior contagion.in addition to the results from radius, in the PO3 region, it can be concluded that this area of the brain may play an important role in the brains of individuals in the Contagion group and sends processed social information faster. previous studies have also shown that the parieto-occipital region is related to the decision-making selection phase, which is corroborated by our findings in this study, showing alignment with previous results (Weinstein, 2023).previous studies have shown that social influence is more related to the DLPFC and TPJ regions, and our data in this study also aligns with previous results and may point to the effective role of these areas in the transmission of others' behavior [4].previous studies have shown that social decision-making is more associated with vmPFC regions, and this area is critical for prosocial decision-making in social decisions. Our findings in this study are consistent with previous results, and we may refer to the role of prosocial decision-making versus antisocial when making decisions regarding the spread of behavior, which is associated with the involvement of this area of the brain(Lockwood et al., 2024). additionally, previous studies have indicated that a specific neural network is engaged in decision-making under social influence, involving the rTPJ, DLPFC, and vmPFC regions. Our data in this study are consistent with these findings, further supporting the role of these brain regions in behavioral contagion and the networked nature of brain function(Hu et al., 2022).moreover, prior research has demonstrated that the occipitoparietal region is associated with social conformity and behavioral contagion. our findings also align with these studies, suggesting the crucial role of this region in the contagion of behavior(Berns et al., 2005).Considering that a significant correlation was observed only in the contagion group between modularity ($r = 0.7$, $p < 0.05$) and radius ($r = 0.6$, $p < 0.05$) with behavioral changes—while this correlation was absent in the no-contagion group—it can be concluded that this relationship may serve as a specific neural marker for behavioral contagion, indicating a neural mechanism underlying social imitation. Therefore, PO3 appears to be a brain region where increased processing differentiation (as reflected by the modularity index) and faster information integration (as indicated by the radius index) could lead to behavior contagion. In addition, given that the predictive indices of VG-based behavior contagion were observed more in the left side of the brain, perhaps it can be said that behavior contagion has laterality in the brain.

one of the limitations of this study is the task design, as we generalized human-computer interaction to human-human interaction. This study lacks face-to-face interaction data and differs from real-world human communication conditions(Ibanez, 2022; Sonkusare et al., 2019). Therefore, future studies are recommended to use hyper-scanning EEG recording, which allows for simultaneous brain activity recording of two individuals(Hakim et al., 2023).considering the different results obtained from various visibility graph parameters across different channels, future research should utilize the visibility graph analysis approach with community detection to better distinguish ERP components(Zheng et al., 2021), especially in studies related to behavioral contagion.Additionally, to account for cultural effects(Henrich et al., 2023), Since culture has a significant impact on the formation of our social norms and our judgment of others, perhaps the influence of culture could be considered important in the behavior contagion. This is because if an altruistic or selfish behavior is to spread, individualistic or collectivistic cultural factors may be involved in our evaluation of the behavior and its contagion. In an individualistic culture, people are more focused on their personal interests and individual goals, whereas in a collectivistic culture, people prioritize the group's benefit. Studies show that people from collectivist cultures (e.g., East Asia, Latin America) tend to give more in the Dictator Game than those from individualist cultures (e.g., U.S., U.K.) (Henrich et al., 2005) . However, given the phenomenon of cultural evolution and the complexity of modern societies (Mesoudi, 2016), further research should be conducted regarding the generalization of results based on community culture, and future studies with larger datasets are recommended. Moreover, given the role of hormones such as oxytocin in social decision-making(Flechsenhar et al., 2024), it is suggested that future research designs incorporate this factor.

Conclusion

In this study, the neural mechanism of behavioral contagion was examined. Using nonlinear time series analysis of ERP with the visibility graph method, we identified a neural marker for behavioral contagion. Specifically, the features modularity and radius showed a direct relationship with behavioral contagion in the group exhibiting this behavior, whereas this relationship was absent in the group without contagion. These findings suggest that modularity and radius can serve as neural predictors of behavioral contagion.

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