

The causal role of temporoparietal junction in computing social influence in human decision-making

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Abstract:

Decision-making in social contexts is commonly driven by two major sources of social influence: normative influence and informational influence. Our previous work has dissociated these two types of social influence, and have identified that bilateral temporoparietal junction (TPJ) encodes normative influence. However, it remains unclear whether the effect of normative influence causally depends on activity in the TPJ. Here, we present a transcranial magnetic stimulation (TMS) study using a similar paradigm in a within-subject design (i.e., right TPJ, left TPJ, and vertex). Behavioral results indicate that disrupting activity in the left TPJ resulted in reduced choice switch probability (i.e., less influenced by dissenting social information), relative to the right TPJ and vertex conditions. Computational modeling with hierarchical Bayesian parameter estimation suggests that the corresponding parameter quantifying normative influence significantly decreased in the left TPJ condition. However, the extent to which informational influence (i.e., social learning) was integrated into individuals' valuation processes was comparable in all three conditions. Together, our results provide evidence for the causal role of left TPJ in computing normative social influence in human decision-making, whereas the integration of informative social influence in value computation remains intact.

Keywords: social influence; transcranial magnetic stimulation (TMS); reinforcement learning; social learning; hierarchical Bayesian modeling.

Introduction

Most human decision-making takes place in a social context, which profoundly influences individual

decision-making processes. In social situations, humans not only make choices according to the expected action-outcome association (e.g., Rangel, Camerer & Montague, 2008), but also tend to align their behavior with others. Behavioral studies have examined social influence as expressed by conformity (Asch, 1951) and have classified two major sources of social influence: normative and informational influence (Cialdini & Goldstein, 2004; Ruff & Fehr, 2014; Toelch & Dolan, 2015). Normative influence leads to public compliance, but individuals may maintain private beliefs, whereas informational influence hypothesizes that social information is integrated into the own valuation process.

Our recent work (Zhang & Gläscher, 2019) has established a comprehensive neuro-computational account of social influence in human decision-making using a novel experimental paradigm. Crucially, we dissociated these two types of social influence, and have identified that bilateral temporoparietal junction (TPJ) encodes normative influence. However, it remains unclear whether the effect of normative influence causally depends on activity in the TPJ. If so, which side? To this aim, we employed the transcranial magnetic stimulation (TMS) technique to investigate the potential causal account between the bilateral TPJ and normative influence. A hierarchical Bayesian approach (Carpenter et al., 2017; Ahn, Haines, & Zhang, 2017) was used to uncover how individuals computed social influence and integrated social information into their own valuation processes.



Methods

Paradigm

We employed a social influence task modified from our previous study (Zhang & Gläscher, 2019). The core of the paradigm was a probabilistic reversal learning (PRL) task. In this two-alternative forced choice PRL, each choice option was associated with a reward probability (i.e., 70% and 30%). After a variable length of trials (i.e., 8-12 trials), the reward contingencies reversed, such that individuals needed to re-adapt to the new reward contingencies in order to maximize their outcome. The social influence task consisted of 3 phases for every trial. *Phase 1. Initial choice (1st choice)*. Upon the presentation of two choice options using abstract fractals, participants were asked to make their 1st choice (3000 ms). A yellow frame was then presented to highlight the chosen option. *Phase 2. Choice adjustment (2nd choice)*. When all four other choices were presented, participants were able to adjust their choices given the social information (3000 ms). The yellow frame was shifted accordingly to highlight the adjusted choice. *Phase 3. Outcome delivery*. Finally, the outcome was determined by participants' 2nd choice (3000 ms plus a jittered inter-trial interval 2000 – 4000 ms; Figure 1).

Different from our previous study (Zhang & Gläscher, 2019) where we conducted a real-time group study, here, only one participant was tested each time. Participants were informed that they were about to play with 4 independent “intelligent computer algorithms” that best matched human behavior in the previous study. In fact, these algorithms were simulated from the winning model in our previous study (Zhang & Gläscher, 2019). Crucially, each algorithm also made two decisions as the participant did: their 1st choice was governed by a combined value signal from direct learning and social learning, whereas their 2nd choice was regulated by the choices of the others. Participants were aware that those computer algorithms were able to learn from trial-and-error, and also took decisions of the others into consideration. To increase ecological validity further, we used human faces to indicate the computer algorithms.

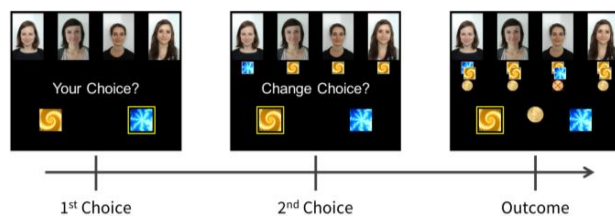


Figure 1: Experimental design.

For each participant, they first played 10 training trials to get familiar with the task procedure, and then played 100 trials per stimulation session (see below). The whole procedure lasted about 2 hours.

Participants

Forty healthy, right-handed participants were invited to participate in the study. No one had any history of neurological and psychiatric diseases, nor current medication except contraceptives. Five participants out of 40 who had either no switch at all or missed more than 20% responses were excluded. The final sample consisted of 35 participants (18 females). All participants gave informed written consent before the experiment. The study was conducted in accordance with the Declaration of Helsinki and was approved by the Ethics Committee of the Medical Association of Hamburg (PV3661).

TMS Stimulation

Stimulation site. We based our stimulation sites on the 2nd-level map of the parametric modulation of dissenting social information from our previous study (Zhang & Gläscher, 2019). The peaks (MNI coordinates) of the bilateral TPJ were identified at $x = 50, y = -60, z = 34$ (right), and $x = -48, y = -62, z = 30$ (left), respectively. Subject-specific stimulation coordinates were obtained using inverse normalization with trilinear interpolation implemented in SPM12, from MNI space to native space. Those coordinates were then superimposed onto each participant's native T1 images. For the control site, we chose the vertex, defined for each participant in their own T1-weighted MRI scan as the intersection of the central sulci from both cerebral hemispheres. Vertex has been commonly used as a control stimulation site as stimulating vertex has minimal task-relevant effects (e.g., Hill et al., 2017; Polania, Nitsche, & Ruff, 2018). Locating subject-specific stimulation sites, as well as creating landmarks of each participant's brain, was implemented with the Brainsight software (Rogue Resolutions Inc Montreal, Quebec, Canada).

Stimulation protocol. We applied a continuous theta-burst stimulation (cTBS; Huang et al., 2005) to the three stimulation sites. We counterbalanced the order of right and left TPJ, and vertex was always in the middle (Figure 2). Following previous literature (e.g., Hill et al., 2017), the cTBS stimulation protocol comprised 600 pulses administered over 40 s in bursts of three pulses at 50 Hz (20 ms), repeated at intervals of 5 Hz (200 ms). Stimulations were controlled and delivered using the Magstim Rapid² stimulator with an air-cooled coil (Magstim Co Ltd. Spring Gardens, Whitland, UK).

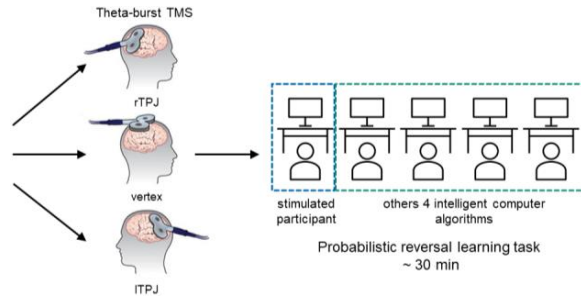


Figure 2: Stimulation protocol and experimental procedure.

Results

Behavioral findings

We first measured the choice switch probability as a function of stimulation site, direction (with vs. against) and group coherence (2:2, 3:1, and 4:0). All two-way interactions were significant: site and direction ($F_{2,475} = 4.17, p = 0.016$), site and coherence ($F_{4,475} = 3.23, p = 0.012$), and direction and coherence ($F_{1,475} = 5.77, p = 0.017$). The three-way interaction was approaching significance ($F_{2,475} = 2.69, p = 0.069$). Further analysis revealed that disrupting activity in the left TPJ resulted in reduced choice switch probability (i.e., less influenced by group disagreement), relative to the right TPJ ($t_{475} = 4.599, p = 0.0008$ Tukey corrected; Figure 3, top).

We next examined the reaction time, also as a function of stimulation site, direction (with vs. against) and group coherence (2:2, 3:1, and 4:0). We found a significant main effect of stimulation site ($F_{2,474} = 5.6, p = 0.0039$). Further analysis indicated that disrupting activity in the left TPJ resulted in prolonged reaction time as compared to the right TPJ condition ($t_{486} = 3.228, p = 0.0038$, Tukey corrected) and the vertex condition ($t_{486} = 3.495, p = 0.0015$, Tukey corrected; Figure 3, bottom).

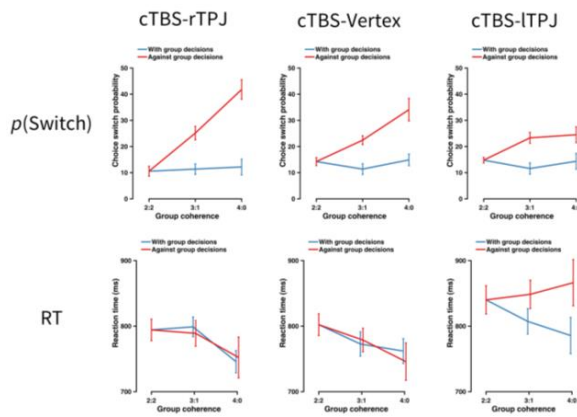
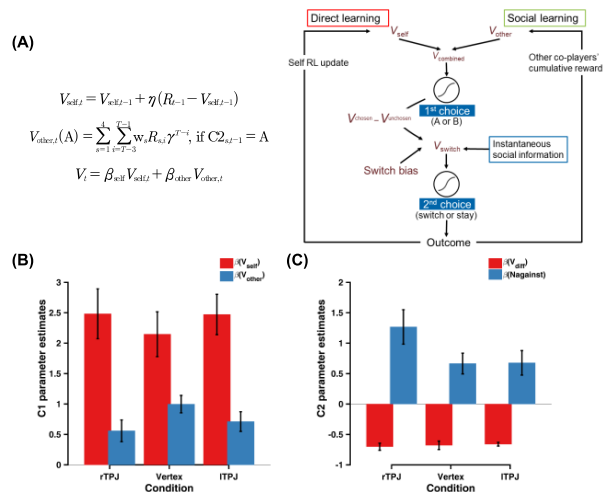


Figure 3: Choice switch probability and reaction time.

Computational modeling

We fit candidate models in the previous study (Zhang & Gläscher, 2019) to the current dataset. Our efforts to construct these models were guided by two design principles: (1) separating of the individual's own value (V_{self}) and the vicarious value of others (V_{other}) during learning, which were then combined into a choice value for the 1st choice ($V_{combined}$), and (2) separating instantaneous normative social influence on the second choice and social learning from observing the performance of other players (i.e., informational influence). Crucially, we modeled the second choice as a function of two counteracting influences: (1) the group dissension ($N_{against}$) representing the instantaneous normative influence and (2) the difference between the participants' action values in the 1st choice ($V^{chosen} - V^{unchosen}$) representing the distinctiveness of the current value estimates (Figure 4A).

Parameter estimate results showed that the degree each participant integrating social learning into their own valuation process were not significantly different across stimulation sites [$\beta(V_{other})$; Figure 4B]. However, participants in the ITPJ condition weighted conflicting social information less when decide whether to switch or stay on their 2nd choice [$\beta(N_{against})$; Figure 4C].



Conclusion

The current study aims to establish the casual account between bilateral TPJ and normative influence in a novel social decision-making task. We found that down-regulating activity in the left TPJ (rather than the right TPJ) resulted in reduced choice switch probability and declined reaction speed when individuals were contradicted by the group (i.e., normative influence). Computational modelling further revealed that the extent to which social learning was integrated into individuals' own valuation processes was intact (i.e., informational influence).

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