Main Manuscript for

Bilateral (but not unilateral) interaction creates and cements norms at the covert psychophysical level: A behavioral and an fMRI study

Authors: Kiri Kuroda^{a,b,1}, Yukiko Ogura^{c,1}, Akitoshi Ogawa^{d,e}, Tomoya Tamei^f, Kazushi Ikeda^g, & Tatsuya Kameda^{a,e,h*}

^aDepartment of Social Psychology, The University of Tokyo, 7-3-1 Hongo, Bunkyo-ku, Tokyo, 113-0033 Japan

^bJapan Society for the Promotion of Science, 5-3-1 Kojimachi, Chiyoda-ku, Tokyo, 102-0083 Japan

^cDepartment of Mechano-Informatics, The University of Tokyo, 7-3-1 Hongo, Bunkyo-ku, Tokyo, 113-0033 Japan

^dFaculty of Medicine, Juntendo University, 2-1-1 Hongo, Bunkyo-ku, Tokyo, 113-8421 Japan

^eBrain Science Institute, Tamagawa University, 6-1-1 Tamagawagakuen, Machida, Tokyo, 194-8610 Japan

^fCenter for Mathematical and Data Sciences, Kobe University, 1-1 Rokkodaicho, Nada-ku, Kobe, Hyogo, 657-8501 Japan

^gDivision of Information Science, Nara Institute of Science and Technology, 8916-5 Takayama, Ikoma, Nara, 630-0192 Japan

^hCenter for Experimental Research in Social Sciences, Hokkaido University, N10W7, Kita-ku, Sapporo, Hokkaido, 060-0810 Japan

*Tatsuya Kameda, Ph.D.

Department of Social Psychology, The University of Tokyo
7-3-1 Hongo, Bunkyo-ku, Tokyo, 113-0033 Japan
+81-3-5841-3868
tkameda@l.u-tokyo.ac.jp

¹K.K. and Y.O. contributed equally to this work.

Author Contributions: K.K., Y.O., A.O., T.T., K.I., and T.K. designed research; T.K. supervised research; K.K., Y.O., A.O., and T.T. performed research; K.K., Y.O., A.O., and T.T. analyzed data; K.K., Y.O., A.O., and T.K. wrote the paper.

Competing Interest Statement: The authors declare no conflict of interest.

Classification: Social Sciences (Psychological and Cognitive Sciences)

Keywords: shared reality, social norms, psychophysical function, mentalizing network, computational models

This PDF file includes:

Main Text
Figures 1 to 3

Abstract

Social norms, including values, beliefs and even perceptions about the world, are preserved and created through repeated interactions between individuals. However, whereas neuro-cognitive research on social norms has used the “unilateral influence” paradigm focusing on people’s reactions to extant standards, little is known about how our basic perceptions and judgments are shaped as new norms through bilateral interaction. Here, using a simple estimation task, we investigated the formation of perceptual norms using two experiments coupled with computational modeling. In the behavioral experiment, participants in dyads repeatedly estimated the number of dots on a screen and viewed each other’s answers. In the fMRI experiment, we manipulated the interaction process by pairing each participant with a computer agent which adjusted its estimations reciprocally to participants’ estimations (bilateral agent) or did not (unilateral). The results indicated that only the bilateral interaction yielded convergence of participants’ covert psychophysical functions (relations between subjective estimations and the actual number of dots) as well as overt behavioral responses within a pair. Bilateral interaction also increased the stability (reliability) of the covert function within each individual after interaction. Neural activity in the mentalizing network (right temporoparietal junction and dorsomedial prefrontal cortex) during interaction modulated the stabilization of the psychophysical function. These results imply that bilateral interaction helps people to cognitively anchor their views with each other. Such spontaneous perspective sharing can yield a shared covert “generative model” that enables endogenous agreement on totally new targets — one of the key features of social norms.

Significance Statement

Understanding how people develop and sustain social norms is important in modern societies where moral divides cause conflict. However, our knowledge about neuro-cognitive processes underlying norm formation remains insufficient, not to mention temporal dynamics during social interaction. Through computational modeling with behavioral and fMRI experiments, we showed that people create and cement perceptual norms not only in overt responses but also in their covert generative models through bilateral interaction. Such a “deep shared reality” allows consensus on totally new targets (not in the learning set) among people immediately, which may further foster their “we-feeling.” Clarifying the level where a shared reality is formed and operates as a social norm is critical to addressing emerging problems in our digitally connected world.

Introduction

Human minds are fundamentally social, requiring continual interaction with others to develop and sustain shared values, beliefs, and even perceptions about the world. Understanding the formation of such “shared realities” (1, 2) or “norms” (3) is important in modern societies where moral divides can cause conflicts. Although there have been studies about how people react to extant norms (see (4–7) for review), little is known about the potential computational mechanisms underlying the dynamic formation of norms through interaction. Here, we address this question experimentally by refining two classic paradigms for studying social norms with modern neuro-cognitive techniques.

In the behavioral and cognitive sciences, norms have often been studied using the Asch conformity paradigm (8). Using a perceptual task, Solomon Asch examined how participants were influenced by unresponsive majorities that repeatedly endorsed objectively wrong answers. The participants conformed to the majority view publicly, but once the group was dissolved, they reverted to their private (correct) answers. This unilateral-influence paradigm is important for understanding norm-compliance/violation and has been used in neuroscience research about social decision making (6, 7). Nevertheless, it assumes that a social norm is given, and does not address how perceptions and judgments are shaped mutually over time.

In another classic experiment, Muzafer Sherif investigated norm formation through bilateral interaction (3). In his study, two or three participants simultaneously viewed a spot of light in a dark room and verbally estimated how much the spot moved. When participants heard each other’s answers, their judgments converged, and they continued to answer the converged value even when performing the task later individually. From these results, Sherif argued that participants developed and internalized “perceptual norms” through interaction.

Sherif’s study is insightful but silent about the computational mechanisms of norm formation (9), because it employed the autokinetic effect (an optical illusion wherein a static spot of light is perceived to be moving in darkness). Because it is impossible to define a psychophysical function (a psychometric relationship between a stimulus and the perceptions/judgments about the stimulus (10)) with this illusion, it is unclear whether bilateral interaction affects only people’s overt responses or may also lead to convergence of the covert psychophysical functions that generate their overt responses.

Here, we investigated neuro-cognitive mechanisms underpinning the formation of perceptual/judgmental norms through dyadic interaction, using a dot-estimation task along with computational modeling. First, in a behavioral experiment, we had pairs of participants work on the estimation task and tested the following hypotheses: (H1) Dyadic interaction

brings about convergence of not only participants' overt responses but also their covert psychophysical functions, within a pair. (H2) Dyadic interaction increases the stability of the psychophysical function within each individual after interaction.

Although rarely studied in previous research, we believe that stabilization of the psychophysical function within each individual (H2) is an important and useful consequence that may accrue from interaction. To illustrate, take the example of a scale with low validity but high reliability of measurement, which always yields a value 10% less than the actual weight. This scale is inaccurate numerically, but still useful for properly ordering items in terms of weight. If stability (reliability) of a psychophysical function increases, it can serve the individual by increasing accuracy of ordering in perceptual judgments.

In a separate fMRI experiment, we intervened in the interaction mechanics. Participants interacted with two "partners" (computer agents), whose behavioral patterns were programmed to follow either Asch-type (unresponsive/one-sided) or Sherif-type (responsive/reciprocal) interactions as sketched earlier. Using a time-series model, we tested the following hypothesis: (H3) Reciprocal concession during interaction (as implemented with the Sherif-type but not with the Asch-type partner) is the key parameter that stabilizes the psychophysical function within each individual after interaction.

Regarding the neural underpinning of H3, fMRI studies have shown that cognitive perspective taking plays a key role in interaction. When interacting with others in a strategic game (11, 12) or in group decision making (13), participants developed internal models about how others decide using the mentalizing network (14) including right temporoparietal junction (RTPJ) and dorsomedial prefrontal cortex (DMPFC). Here, we conjecture that participants adjust their judgments during bilateral interaction by anchoring their views with the partner's views via perspective taking. As suggested by Sherif (3), such perspective taking may help stabilize each participant's psychophysical function. We thus hypothesize: (H4) Activity of the mentalizing network during bilateral interaction modulates stabilization of the psychophysical function within each individual after interaction.

Behavioral Experiment

Task. Sixty-three participants performed a dot-estimation task. In each trial, participants were presented with 25-55 randomly sized and colored dots for 0.8 second and then asked to estimate the number of dots (Fig. 1A). No feedback was given to participants about their estimation accuracy.

There were three phases in the experiment (Fig. 1A). In Phases 1 and 3 (hereafter solo phases), all participants performed 16 trials individually. In Phase 2 there were 144 trials, and participants were randomly assigned to either the individual or pair condition. Participants in the individual condition performed the task individually again as a control. In each trial of the pair condition ($N = 42$), two participants observed the same dots and answered independently and then were shown both their own and the other's estimates. The pairs were instructed that they did not need to give similar estimates and that each participant's reward would depend entirely on his/her own estimation accuracy. Participants remained anonymous to each other and were allowed no verbal communication.

Results.

Modeling a participant's psychophysical function. We first approximated participant i 's dot estimation at trial t , $Est_i(t)$, by a linear psychophysical model:

$$Est_i(t) = w_i \times DotNum(t) + \varepsilon, \quad (1)$$

where w_i denotes the participant's estimation weight, $DotNum$ denotes the number of dots, and ε denotes Gaussian noise (see Table S1 for performance of this model compared to a log-linear model in Eq. S1). The estimation weight is less (greater) than 1 if the participant underestimates (overestimates) the number of dots.

We calculated estimation weights (w_i) for participants in the pair condition for Phases 1 and 3 (solo phases) separately using the maximum likelihood method. As seen in Fig. 1B, on average participants exhibited an underestimation bias (15) in Phase 1 ($w = 0.915 \pm 0.200$: one-sample $t_{(41)} = 2.75$, $P = .009$) and retained this bias uncorrected in Phase 3 after the interaction ($w = 0.912 \pm 0.185$: one-sample $t_{(41)} = 3.08$, $P = .004$).

Convergence of psychophysical functions within pairs through interaction (H1). For each pair, we calculated the absolute difference between the two participants' estimation weights in Phases 1 and 3 (solo phases). The mean absolute difference decreased significantly after the interaction in Phase 2 (Fig. 1C left; paired $t_{(20)} = 2.81$, $P = .011$).

However, mere task repetition rather than interaction could have yielded this convergence. We thus created 210 nominal pairs from 21 participants in the individual condition and compared each nominal pair's absolute difference in estimation weights between Phases 1 and 3. No significant change was found between the phases (Fig. 1C right; paired $t_{(209)} = 1.10$, $P = .275$). The decrease was also larger in the real pairs than in the nominal pairs (Welch's $t_{(24.1)} = 3.01$, $P = .006$). These results support the contention in H1 that the individual psychophysical functions converge through social interaction.

Stabilization of the psychophysical function within each individual through interaction (H2). The results so far indicate that interaction yielded convergence at the pair level (Fig. 1C) but did not correct the systematic underestimation bias at the individual level (Fig. 1B). However, even if the estimation accuracy per se is not improved, interaction may increase the stability of the psychophysical function within each individual. As illustrated with the scale metaphor earlier, such stabilization could serve to improve accuracy in ordering of targets, even if estimations remain biased numerically. To address this point, we performed the following analysis (see Fig. 1D for illustration). We divided the 16 trials of Phases 1 and 3 separately into four subsets of four consecutive trials each and estimated each participant's estimation weight (w_{ij}) for subset j . Then, across the four subsets, we calculated the standard deviation (SD) of estimation weights. A smaller SD indicates a more stable (reliable) psychophysical function in the phase.

Figure 1E shows that the SD decreased significantly from Phase 1 to 3 in the pair condition (paired $t_{(41)} = 2.92$, $P = .006$), but not in the individual condition (paired $t_{(20)} = 0.62$, $P = .544$). The decrease in SD was larger in the pair condition than in the individual condition (Welch's $t_{(37.9)} = 2.13$, $P = .040$). These results support H2's claim that pair interaction stabilizes the psychophysical function within each individual.

These patterns are in line with our arguments. However, it remains to be seen what behavioral and neuro-cognitive processes underlay the convergence and stabilization of the individual psychophysical functions through interaction. We conjecture that reciprocal behavioral concession and cognitive perspective-taking (associated with activation of the mentalizing network) during interaction are key for these phenomena. To address these conjectures, we conducted an fMRI experiment in which we manipulated the paired interaction patterns. Participants interacted with two "partners" (computer agents), whose response patterns were pre-programmed to exhibit reciprocal concession ("Sherif-type") or not ("Asch-type").

fMRI Experiment

Task. Twenty-eight participants performed the dot-estimation task. The experiment consisted of one pre-interaction phase (24 trials), two interaction phases (48 trials each), and two post-interaction phases (24 trials each; Fig. 2A). In the pre-interaction phase, participants performed the task individually as in the solo phases of the behavioral experiment (Fig. S1).

For the two interaction phases, we developed two computer partners — the Sherif- and Asch-type partners. In each interaction phase, participants were paired with a computer

partner described as “another participant.” In each trial, the participant and the computer partner estimated the number of dots independently, and then their estimates were shared as in the behavioral experiment (Fig. S1). Although both computer partners had a strong underestimation bias initially ($w = 0.61$) compared to the average participant of the behavioral experiment (mean $w = 0.91$; Fig. 1B), they were programmed to differ in their reciprocity to participants’ estimates during interaction (see *SI Methods* for details). The Asch-type partner retained its underestimation bias throughout trials irrespective of the participant’s estimates (8) (Eq. S2). In contrast, the Sherif-type partner adjusted its weight over trials toward the participant’s estimates (3). The Sherif-type partner was designed to approximate the pattern of an average participant’s estimation-adjustment in the behavioral experiment (Eq. S3).

In the two post-interaction phases, participants worked on the task individually again as in the pre-interaction phase. Hereafter, we use the terms “post-Sherif phase” and “post-Asch phase” to refer to each post-interaction phase (Fig. 2A).

Results.

Reciprocal concession stabilizes the psychophysical function within each individual after interaction (H3). To see how participants responded to the two computer partners, we first calculated estimation weights (w_i in Eq. 1) for the pre-interaction, post-Sherif, and post-Asch phases separately for each participant using the maximum likelihood method. Figure 2B shows that, for both kinds of partners, participants’ estimation weights decreased after interaction (post-Sherif: paired $t_{(27)} = 2.35$, $P = .053$; post-Asch: paired $t_{(27)} = 3.87$, $P = .002$ after Holm-Bonferroni correction). No significant difference was observed between the partners (paired $t_{(27)} = 1.55$, Holm-Bonferroni corrected $P = .132$). These results indicate that participants were equally influenced by both partners and increased their underestimation biases through interaction.

However, as expected, the Sherif- and Asch-type partners had different impacts on the stability of the psychophysical function for each individual (indexed by the *SD* of estimation weights as in the behavioral experiment). As seen in Fig. 2C, compared to the pre-interaction phase, individual estimation weights were more stable after interacting with the reciprocal Sherif-type partner (paired $t_{(27)} = 3.46$, Holm-Bonferroni corrected $P = .005$), but not with the non-reciprocal Asch-type partner (paired $t_{(27)} = 0.82$, Holm-Bonferroni corrected $P = .420$). The difference between the two partners was marginally significant (paired $t_{(27)} = 2.14$, Holm-Bonferroni corrected $P = .083$). These results support H3. Reciprocal concession, as

implemented with the Sherif-type partner, led to stabilization of participants' psychophysical functions.

Time-series analysis of updating estimation weight during interaction. To examine the cognitive dynamics underlying the different impacts of the Sherif- and Asch-type partners (Fig. 2C), we analyzed how participants updated their estimation weights during interaction using a time-series model (see *SI methods* and Eqs. S4-6 for details). In the model, a participant's estimation weight (w_i in Eq. 1) in trial t was further decomposed into three parameters:

$$w_i(t) = \text{Baseline} + \text{Coef}_{\text{Atyp}}(t) \times \text{Atyp}(t - 1) + \text{Coef}_{\text{Sim}}(t) \times \text{Sim}(t - 1), \quad (2)$$

where *Baseline* (i.e., intercept) indicates the participant's estimate without social influence, and *Atypicality* (*Atyp*) is a nuisance parameter that controls for effect of the built-in strong underestimation bias of the computer partner (Eq. S5).

Similarity (*Sim*) represents closeness between the participant's estimate and the partner's estimate in the preceding trial (Eq. S6). As we are concerned with reciprocal concession over time (H3), *Similarity* is the parameter of interest in our analysis. That is, the coefficient for *Similarity* (Coef_{Sim}) indicates how the participant updates the estimation weight in response to the similarity between their own estimate and the partner's estimate in the preceding trial. As the computer partner initially had a stronger underestimation bias ($w = 0.61$) than the average participant ($w = 0.91$), a negative coefficient means that the participant approaches the partner (i.e., decreases his/her estimation weight) in the current trial, whereas a positive coefficient means the opposite shift, in response to the preceding similarity with the partner.

Figure 2D shows that the coefficient for *Similarity* was negative when participants interacted with the Sherif-type partner ($M = -0.06$, one-sample $t_{(27)} = 3.46$, $P = .002$), and positive when interacting with the Asch-type partner ($M = 0.09$, one-sample $t_{(27)} = 3.19$, $P = .002$). In addition, the coefficients were significantly different between the two partners (paired $t_{(27)} = 5.46$, $P < .001$). These results are also in line with H3. When interacting with the Sherif-type partner, larger similarity in the preceding trial fostered more similarity in the current trial (i.e., reciprocal concession). In contrast, when interacting with the Asch-type partner, participants moved away from the partner in response to the preceding similarity.

Activity of the mentalizing network during bilateral interaction modulates stabilization of an individual's psychophysical function after interaction (H4). To test H4's claim that perspective-taking underpins the different impacts between the Sherif- and Asch-

type partners (Fig. 2C & 2D), we focused on activations of the mentalizing network including RTPJ and DMPFC. The regions of interest (ROIs) in RTPJ and DMPFC were defined for each participant using a functional localizer for cognitive perspective taking (16, 17). Using the individual ROIs, we examined activities of the RTPJ and the DMPFC while participants interacted with the two computer partners (Figs. 3A & S3; see *SI Methods* for details).

We first analyzed brain activity during interaction at the group level. Figure 3B shows that RTPJ activity tracked *Similarity* in estimation in the preceding trial (see Eqs. S4 & S6) when participants interacted with the Sherif-type partner (one-sample $t_{(27)} = 2.63$, $P = .021$), but not with the Asch-type partner (one-sample $t_{(27)} = 0.69$, $P = .495$); the difference between the two types was also significant (paired $t_{(27)} = 2.25$, $P = .033$). These RTPJ activity patterns are consistent with the behavioral responses (Fig. 2D). Figure 3C indicates that the DMPFC tracked participant's output (*Estimation*) in the current trial ($Est_i(t)$ in Eq. S4) when interacting with the Sherif-type partner (one-sample $t_{(27)} = 2.05$, $P = .050$) and the Asch-type partner (one-sample $t_{(27)} = 2.29$, $P = .030$), with larger activation for larger estimates.

Next, we analyzed the relation between brain activity during interaction and the stability (*SD*) of the psychophysical function in post-interaction (Fig. 2C) at the individual level. Figure 3D shows that the RTPJ activity in response to *Similarity* during interaction (Fig. 3B) correlated with the stability of estimation in the post-Sherif phase (robust correlation $r = -.32$, $P = .049$) but not in the post-Asch phase (robust correlation $r = .06$, $P = .774$). To observe the role of the mentalizing network, we examined the contribution of the RTPJ-DMPFC functional connectivity on the stability of estimation using a psychophysiological interaction analysis (see *SI methods*). As seen in Fig. 3E, the RTPJ-DMPFC functional connectivity during interaction correlated with stability in the post-Sherif phase (robust correlation $r = -.57$, $P = .005$) but not in the post-Asch phase (robust correlation $r = .02$, $P = .928$).

These results support H4. As expected, the mentalizing network was activated according to *Similarity* (Eq. S6) when participants interacted with the reciprocal Sherif-type partner, but not with the non-reciprocal Asch-type partner (Fig. 3B). Reciprocal concession during interaction (as indexed behaviorally by the negative coefficient for *Similarity* with the Sherif-type partner: Fig. 2D) was key for spontaneous perspective taking about the partner (Fig. 3B), which in turn contributed to the stabilization of the participant's own psychophysical function after the interaction (Figs. 2C, 3D & 3E).

Discussion

Most previous studies on social influence have adopted an Asch-like unilateral paradigm (8) to investigate how individuals comply or violate extant norms (4–7). However, few studies have directly addressed neuro-cognitive underpinnings of dynamic norm-formation through mutual influence. We hypothesized that, using perspective-taking, perceptions and judgments are shaped as a shared norm by bilateral (but not unilateral) interaction, and tested this claim using behavioral and fMRI experiments coupled with computational modeling.

The results supported our hypotheses. In the behavioral experiment using real pairs, dyadic interaction yielded pairwise convergence of not only participants' overt behavioral responses but also their covert psychophysical functions (H1: Fig. 1C). The paired interaction also stabilized the psychophysical function within each individual as an aftereffect (H2: Fig. 1E). Note that participants were not instructed to match their estimates with each other, but only asked to provide accurate individual estimates in order to obtain their own rewards. This indicates that the convergence and stabilization of covert psychophysical functions were not enforced exogenously but rather emerged endogenously through social interaction.

In the fMRI experiment, we created two types of computer partners: reciprocal Sherif-type (similar to most participants in the behavioral experiment) and non-reciprocal Asch-type. While participants' estimates were equally affected by both partners (Fig. 2B), each individual's psychophysical function was stabilized after interacting with the Sherif-type but not with the Asch-type partner (Fig. 2C). In addition, participants adjusted their estimation weights reciprocally during interaction only with the Sherif-type partner (Fig. 2D).

At the neural level, the mentalizing network contributed to the dynamic formation and stabilization of social norms. Firstly, consistent with the behavioral results (Fig. 2D), RTPJ activity tracked temporal changes in estimation similarity with the reciprocal Sherif-type partner but not the one-sided Asch-type partner (Fig. 3B). Such RTPJ activity when paired with the reciprocal partner also contributed to the stabilization of participants' own covert psychophysical functions afterwards (Fig. 3D). The RTPJ region we focused on here (Fig. 3A) has been shown to be associated with inference of another's intention (18). Our finding suggests that such inference may also extend to inference of another's covert psychophysical function that generates judgments from shared stimuli.

Secondly, we observed that DMPFC activity tracked how participants expressed their estimations during interaction (i.e., larger activation when giving larger estimates: Fig. 3C). It might be the case that expressing larger estimation in the presence of a partner with a strong

underestimation bias was a socially nuanced action, which seems to concur with the previous finding that the DMPFC modulates self-related evaluation (19) embedded in social contexts (20–22).

Lastly, RTPJ-DMPFC functional connectivity modulated stabilization of participants' psychophysical functions after interacting with the reciprocal Sherif-type partner (Fig. 3E). It is noteworthy that both the DMPFC and RTPJ regions defined in this study overlap with the regions for spontaneous mentalizing about others; that is, these regions are known to be recruited even when participants are not explicitly instructed to infer another's mental state (23–26). Our participants were also instructed that they did not need to give similar estimates and that their reward would depend entirely on own estimation accuracy. Taken together, interaction with a reciprocal partner seems to facilitate spontaneous activation of the mentalizing network. These results support H3 and H4.

In summary, reciprocal behavioral concession seems to lead us to take the perspective of our interaction partners. Such spontaneous switching between one's own and another's view about shared targets may increase the stability of our psychophysical functions, as triangulation measurement serves for reliably determining the location of a point.

We believe that these results are significant in two respects. Firstly, in our rapidly changing societies, social norms are also changing constantly. Research on formation of new norms (as opposed to acquisition of extant norms) is of keen importance, including rapid development of “shared reality” on the internet. According to (2), shared reality is not a mere duplication or “catching” of another person's response – it requires mechanisms to infer the partner's inner state along with its target referent; mechanisms used to infer others' mental states include conscious reasoning, unconscious simulation, and theory of mind. Our finding that bilateral interaction brings about convergence of not only overt behavioral responses but also covert psychophysical functions via perspective taking fits this definition. It is also noteworthy that a shared psychophysical function allows us to agree on a totally new target (not in the original “learning set”) immediately, without interaction. These generalized endogenous agreements may further foster a shared sense that we feel and think the same way. We believe that such a shared “generative model” (27) is one of the fundamental components of social norms (28, 29).

Secondly, our results seem to shed new light on group decision making and its accuracy (the so-called wisdom of crowds (WoC): (30)). Previous research on WoC has yielded mixed results regarding the effect of interaction, with some showing negative impacts (31) and others reporting positive impacts (15). Moreover, although most WoC research has

focused on improved accuracy in aggregated numeric judgments (32, 33), aggregating ordered choices has also been shown to yield WoC (34, 35). The present study has shown that, although interaction did not correct people's underestimation bias per se (Figs. 1B & 2B), bilateral (but not unilateral) interaction stabilized their psychophysical functions (Fig. 2C). Recall that, as illustrated with the weighing metaphor, an increase in stability (reliability) of the psychophysical function improves the accuracy of ordering of estimation targets. In other words, even though people remain biased numerically, bilateral interaction improves individual ordering of the targets over time and may enhance accuracy of group choice (e.g., aggregated ordering by majority/plurality voting). Future research on group-decision accuracy from this perspective seems promising.

We rely on constant interaction with others for the development and sustenance of our shared realities (1, 2). Extending the computational approach from "perceptual" norms (3) as studied here to more social ones (about values and morals), while focusing on the formation of shared "generative models" (27), seems critical to better understand emerging problems in our digitally connected but often morally divided world.

Methods

This study was approved by the Ethics Committee of the Department of Social Psychology at the University of Tokyo, and all participants gave written informed consent. See Supplementary Information for details of the procedures and analysis.

In the behavioral experiment (Fig. 1A), 63 participants were presented with 25–55 randomly sized and colored dots for 0.8 second and then asked to estimate the number of dots in each trial. The experiment consisted of three phases, and there were 16 trials each in Phases 1 and 3 for analysis. Phase 2 had 144 trials in order to generate sufficient data to implement average participant behavior as a computer agent later for the fMRI experiment. In Phases 1 and 3, all participants estimated the number of dots individually. In Phase 2, 21 participants performed the task individually again as a control, and the remaining 42 participants performed the task in pairs. Each pair observed the same dots and estimated the number of dots individually, and then each viewed both their own and the partner's estimates. No feedback was given to participants about their estimation accuracy. After the experiment, participants were paid according to their respective individual performances.

We scanned 28 participants in the fMRI experiment (Figs. 2A & S1). The experiment consisted of one pre-interaction phase, two interaction phases, and two post-interaction phases (24, 48, and 24 trials, respectively). In the pre- and post-interaction phases, each

participant performed the dot-estimation task individually. In each interaction phase, the participant was paired with the Sherif- or Asch-type computer partner, which was described as “another participant.” The participant and the computer partner estimated the number of dots independently, and then both estimates were shown after every trial. The Sherif-type partner adjusted its estimation weights in response to the participant during interaction, whereas the Asch-type partner remained unaffected by the participant’s estimates throughout the phase. No feedback was given to participants about their estimation accuracy. To identify individual ROIs in the RTPJ and the DMPFC, we conducted a localizer task for cognitive perspective taking, separate from the main task. Using the individual ROIs, we examined whether the RTPJ tracked *Similarity* and whether the DMPFC tracked *Estimation* during interaction. We also examined functional RTPJ-DMPFC connectivity to see whether the RTPJ activity tracking *Similarity* modulated the DMPFC activity. At the end of the experiment, participants were debriefed and paid according to their performances.

Acknowledgments. This study was supported by Japan Society for the Promotion of Science (JP16H0632 to T.K. and JP1821510 to K.K.) and Japan Science and Technology Agency CREST (JPMJCR17A4 (17941861) to T.K.). We appreciate support from UTokyo Center for Integrative Science of Human Behavior.

References

1. E. T. Higgins, *Shared reality: What makes us strong and tears us apart*. (Oxford University Press, 2019).
2. G. Echterhoff, E. T. Higgins, Shared reality: Construct and mechanisms. *Curr. Opin. Psychol.* **23**, iv–vii (2018).
3. M. Sherif, *The psychology of social norms* (Harper & Brothers, 1936).
4. R. B. Cialdini, N. J. Goldstein, Social influence: Compliance and conformity. *Annu. Rev. Psychol.* **55**, 591–621 (2004).
5. R. Bond, P. B. Smith, Culture and conformity: A meta-analysis of studies using asch's (1952b, 1956) line judgment task. *Psychol. Bull.* **119**, 111–137 (1996).
6. H. Wu, Y. Luo, C. Feng, Neural signatures of social conformity: A coordinate-based activation likelihood estimation meta-analysis of functional brain imaging studies. *Neurosci. Biobehav. Rev.* **71**, 101–111 (2016).
7. U. Toelch, R. J. Dolan, Informational and normative influences in conformity from a neurocomputational perspective. *Trends Cogn. Sci.* **19**, 579–589 (2015).
8. S. E. Asch, Studies of independence and conformity: I. A minority of one against a unanimous majority. *Psychol. Monogr. Gen. Appl.* **70**, 1–70 (1956).
9. M. J. Crockett, How formal models can illuminate mechanisms of moral judgment and decision making. *Curr. Dir. Psychol. Sci.* **25**, 85–90 (2016).
10. G. R. van den Bos, *APA dictionary of psychology*. (American Psychological Association, 2007).
11. A. N. Hampton, P. Bossaerts, J. P. O'Doherty, Neural correlates of mentalizing-related computations during strategic interactions in humans. *Proc. Natl. Acad. Sci. U. S. A.* **105**, 6741–6746 (2008).
12. A. Ogawa, T. Kameda, Dissociable roles of left and right temporoparietal junction in strategic competitive interaction. *Soc. Cogn. Affect. Neurosci.* **14**, 1037–1048 (2019).
13. S. Suzuki, R. Adachi, S. Dunne, P. Bossaerts, J. P. O'Doherty, Neural mechanisms underlying human consensus decision-making. *Neuron* **86**, 591–602 (2015).
14. C. D. Frith, U. Frith, The neural basis of mentalizing. *Neuron* **50**, 531–534 (2006).
15. B. Jayles, *et al.*, How social information can improve estimation accuracy in human groups. *Proc. Natl. Acad. Sci.* **114**, 12620–12625 (2017).
16. D. Dodell-Feder, J. Koster-Hale, M. Bedny, R. Saxe, fMRI item analysis in a theory of mind task. *NeuroImage* **55**, 705–712 (2011).
17. A. Ogawa, A. Ueshima, K. Inukai, T. Kameda, Deciding for others as a neutral party recruits risk-neutral perspective-taking: Model-based behavioral and fMRI experiments. *Sci. Rep.* **8**, 1–10 (2018).
18. M. I. Gobbini, A. C. Koralek, R. E. Bryan, K. J. Montgomery, J. V. Haxby, Two takes on the social brain: A comparison of theory of mind tasks. *J. Cogn. Neurosci.* **19**, 1803–1814 (2007).
19. D. A. Gusnard, E. Akbudak, G. L. Shulman, M. E. Raichle, Medial prefrontal cortex and self-referential mental activity: Relation to a default mode of brain function. *Proc. Natl. Acad. Sci. U. S. A.* **98**, 4259–4264 (2001).
20. D. M. Amodio, C. D. Frith, Meeting of minds: The medial frontal cortex and social cognition. *Nat. Rev. Neurosci.* **7**, 268–277 (2006).
21. G. Northoff, *et al.*, Self-referential processing in our brain—A meta-analysis of imaging studies on the self. *NeuroImage* **31**, 440–457 (2006).
22. L. van der Meer, S. Costafreda, A. Aleman, A. S. David, Self-reflection and the brain: A theoretical review and meta-analysis of neuroimaging studies with implications for schizophrenia. *Neurosci. Biobehav. Rev.* **34**, 935–946 (2010).

23. J. Kestemont, M. Vandekerckhove, N. Ma, N. Van Hoeck, F. Van Overwalle, Situation and person attributions under spontaneous and intentional instructions: An fMRI study. *Soc. Cogn. Affect. Neurosci.* **8**, 481–493 (2013).
24. F. Van Overwalle, M. Vandekerckhove, Implicit and explicit social mentalizing: Dual processes driven by a shared neural network. *Front. Hum. Neurosci.* **7**, 1–6 (2013).
25. C. Moessnang, *et al.*, Differential responses of the dorsomedial prefrontal cortex and right posterior superior temporal sulcus to spontaneous mentalizing. *Hum. Brain Mapp.* **38**, 3791–3803 (2017).
26. T. Kameda, *et al.*, Rawlsian maximin rule operates as a common cognitive anchor in distributive justice and risky decisions. *Proc. Natl. Acad. Sci.* **113**, 11817–11822 (2016).
27. D. Hassabis, D. Kumaran, C. Summerfield, M. Botvinick, Neuroscience-inspired artificial intelligence. *Neuron* **95**, 245–258 (2017).
28. S. Bowles, Endogenous preferences: The cultural consequences of markets and other economic institutions. *J. Econ. Lit.* **36**, 75–111 (1998).
29. E. Ostrom, Collective action and the evolution of social norms. *J. Econ. Perspect.* **14**, 137–158 (2000).
30. J. Surowiecki, *The wisdom of crowds* (Knopf Doubleday Publishing Group, 2005).
31. J. Lorenz, H. Rauhut, F. Schweitzer, D. Helbing, How social influence can undermine the wisdom of crowd effect. *Proc. Natl. Acad. Sci.* **108**, 9020–9025 (2011).
32. F. Galton, Vox populi. *Nature* **75**, 450–451 (1907).
33. S. Krause, R. James, J. J. Faria, G. D. Ruxton, J. Krause, Swarm intelligence in humans: diversity can trump ability. *Anim. Behav.* **81**, 941–948 (2011).
34. R. Hastie, T. Kameda, The robust beauty of majority rules in group decisions. *Psychol. Rev.* **112**, 494–508 (2005).
35. T. Kameda, T. Tsukasaki, R. Hastie, N. Berg, Democracy under uncertainty: The wisdom of crowds and the free-rider problem in group decision making. *Psychol. Rev.* **118**, 76–96 (2011).

515
516 **Figure 1.** Task and results from the behavioral experiment. (A) Timelines of the dot-
517 estimation task. In Phases 1 and 3 (solo phases), all participants estimated the number of dots
518 individually. In Phase 2, 21 participants in the individual condition performed the task
519 individually again as a control. Those in the pair condition ($N = 42$) observed the same dots
520 and estimated the number of dots independently, and then their estimates were shared with
521 each other. (B) Participants' estimation weights (w_i) in Phases 1 and 3 in the pair condition.
522 Each point indicates one participant's estimation weight. (C) Absolute differences in
523 estimation weights between two participants of the real and nominal pairs in Phases 1 and 3
524 (mean $\pm$ SEM across pairs). $*P < .05$. (D) An illustration of increased stability of a
525 participant's estimation weight from Phase 1 to 3, as indexed by decrease in the standard
526 deviation (SD). First, we divided the 16 trials of each phase into four subsets of four
527 consecutive trials each. Next, we estimated the participant's estimation weight for each
528 subset and then calculated the SD of the four estimation weights in each phase. Each point in
529 the illustration represents an estimation weight in each subset. (E) SD s of estimation weights
530 in the pair and individual conditions (mean $\pm$ SEM across participants). $**P < .01$.

Figure 2. Task flow and behavioral results from the fMRI experiment. (A) The flow of the fMRI experiment. In the pre- and post-interaction phases, participants performed the dot-estimation task individually. In each interaction phase, the participant was paired with the Sherif- or Asch-type partner. The order of the two partners was counterbalanced across participants. The participant and the partner observed the same dots and estimated the number of dots independently, and then their estimates were shared. (B) Participants' estimation weights (w_i) in each phase. Each point indicates one participant's estimation weight. (C) SDs of estimation weights, indexing stability of the participant's psychophysical function (mean $\pm$ SEM across participants). $\dagger P < .10$, $**P < .01$. (D) Coefficients for *Similarity* for the two computer partners (mean $\pm$ SEM across participants) in the time-series analysis of participant's estimates during interaction. $**P < .01$, $***P < .001$.

Figure 3. Imaging results from the fMRI experiment. (A) Individual RTPJ and DMPFC ROIs identified by the functional localizer for cognitive perspective taking. The color bar shows the number of overlapped individual ROIs in each voxel. (B) Parametric modulation for *Similarity* (Eq. S6) in RTPJ activity during interaction (mean $\pm$ SEM across participants). $*P < .05$. (C) Parametric modulation for *Estimation* (Eq. S4) in DMPFC activity (mean $\pm$ SEM across participants) during interaction, with larger activation for larger estimates. $\dagger P < .10$, $*P < .05$. (D) Correlations between RTPJ betas (in response to *Similarity* during interaction: Fig. 3B) and the stability (*SD*) of the participants' estimation weights in post-interaction. $*P < .05$. (E) Correlations between RTPJ-DMPFC functional connectivity during interaction and the stability (*SD*) of the participants' estimation weights in post-interaction. $**P < .01$.