The Effects of Social Communication Dynamics on Opinion Change

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Many social interactions are characterised by dynamic interplay, such that individuals exert reciprocal influence over each other's behaviours and opinions. The present study investigated how the dynamics of reciprocal influence affect decisions made in a social context, over and above the information communicated in an interaction. To this end, we developed a simple social decision-making paradigm in which two people are asked to make perceptual judgments while receiving information about each other's decisions. In a Static condition, information about the partner only conveyed their initial, independent judgment. However, in a Dynamic condition, each individual saw the evolving opinion of their partner as they learnt about and responded to the individual's own judgment. The results indicated that in both conditions, the majority of confidence adjustments followed a step function characterised by an abrupt change followed by smaller adjustments around an equilibrium, and that participants' confidence was used to arbitrate conflict (although deviating from Bayesian norm). Crucially, interaction had systematic effects on opinion change relative to the Static baseline, magnifying confidence change when partners agreed and reducing confidence change when they disagreed. These findings indicate that during dynamic interactions—often a characteristic of real-life and online social contexts—information is collectively transformed rather than acted upon by individuals in isolation. Consequently, the output of social events is not only influenced by what the dyad knows but also by predictable non-linear and self-reinforcing dynamics.

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Introduction

People very often rely on others' judgments to inform their decisions. We ask our family and friends what they think about a particular job we are planning to apply for, the colour of a new dress to buy, or the political candidate to favour. When information is costly to acquire, aggregating multiple samples of imprecise information is often more effective than spending time improving a single sample (1). Aggregating opinions from diverse and independent sources has long been known to improve judgment reliability (2, 3). How people do this, to incorporate others' opinions and advice into their decisions, has long been of central interest in social and organisational psychology (4, 5) and more recently in computational social science (6–8). One particularly fruitful approach to this question is the judge-advisor system paradigm (5, 9, 10), in which participants (the "judges") form independent opinions, then are asked to revise their initial judgment

after seeing the opinion of one or more advisors. This approach provides precise control over the information provided by the advice to participants, as well as precisely defined and distinct moments at which an initial decision is formed, advice is presented, and the judge's opinion updated. Leveraging this experimental precision, previous studies have highlighted the factors affecting how personal judgments are influenced by others' opinions, like confidence (11, 12), power (13, 14), expertise (15), agreement among different sources (16), whether the self is involved (17, 18) and how distant is the advice from the judge's own view (19–21).

However, in daily life, advisors' opinions rarely remain independent from each other or from the advisee's own judgment, as is typically implemented in judge-advisor system studies. Instead, information is collectively transformed and manipulated until it converges to a decision. For example, you might say to the friend recommending the yellow dress that you actually don't like yellow, you like green; to which she replies that she thought green was kind of nice too and when, at that point, a member of staff at the shop interrupts to say that green is going to be next year's fashionable colour, a purchase is made. Here, the processes of decision, advice and update take place all at the same time, and the line between judge and advisors blurs such that all partners affect each other's opinions without a clear distinction between cause and effect. Thus, in social contexts, interaction may happen on a continuous time scale rather than in discrete time steps, raising the possibility of non-linear dynamics.

As such, a full picture of social decision making may require analysis of interaction dynamics, moving beyond the very valuable simplification of a participant working alone as an observer of social information (cf. 22–26). Consistent with this reasoning, previous work found that individuals performing a task together become more confident and align their linguistic expressions when they are allowed face-to-face verbal interaction but not when confidence is shared without verbal interaction (27, 28). The finding relates back to earlier work in social psychology on "risky shifts" and group polarisation (29–31). However, little is known about the direct comparison between continuous and discrete social exchange. To address this issue, in the present study we investigated differences between static vs. dynamic interactions in social decision making, specifically in a task in which the information available to participants to make a decision was kept constant

across interactions, thus allowing us to characterize the specific impact of interaction dynamics themselves, above and beyond the information brought to the interaction by the individuals involved.

In our study, participants performed simple perceptual judgements in a social scenario characterised by two people performing the task in parallel. On each trial, participants first made private, independent judgments (about which of two boxes contained more dots (32)), and then were allowed to update their judgement, expressed on a semi-continuous confidence scale, based on observing the other participant's opinion (on the same scale). Each participant was thus both judge and advisor, allowing us to monitor confidence changes and influence in a system characterised by two-way information exchange (22). Importantly, we compared conditions characterised by static information exchange—in which participants only saw their partner's initial judgment—with conditions characterised by dynamic information exchange—in which participants saw their partner's moment-by-moment opinion change and thus how they themselves influenced their partner's views. By keeping decision-relevant information constant in the two conditions, it is possible to isolate the contrast between static and dynamically evolving advice, and thus characterise the way information is shared and collectively transformed between advisors. Based on recent proposals in the literature (22, 24–26), our key prediction is that changing the directionality and dynamics of the information exchange (bi-directional vs. one-way; recursive vs. static) will affect the final judgments that participants will converge to after social exchange, even though the perceptual evidence accumulated during the private phase is the only information needed to successfully accomplish the task, and this evidence is matched across the two conditions.

Three experiments ($N = 72$) were performed. Experiment 1 directly compares interactive and static situations within dyads. Key differences are found between the two, suggesting that when participants are allowed to freely interact in real-time, non-linearities in the confidence update are observed. Experiments 2 and 3 (reported in Supplementary Information) largely replicate the findings of Experiment 1, adding controls for potential confounding factors, specifically that the key effects of the first study were due to failures in the maintenance in working-memory of one's own (Experiment 2) and one's partner's (Experiment 3) opinion. They also reproduce the key results using different instructions and a different confidence scale, thus indicating that the results are robust across different settings.

Methods

Participants. Twenty-four dyads ($N = 48$, 37 females, age: $M = 22.52$, $STD = 3.16$) were recruited in pairs for money or course credits, through local announcements and the University of Oxford volunteers platform. The invitation informed potential volunteers to bring a friend of the same gender. This was done to avoid confounds due to gender differences in the use of confidence scales and it represents standard practice in

the literature (33, 34). All dyads responded positively to the call, apart for one whose members were gender mixed due to unforeseen circumstances. The study was approved by local ethical committee. All participants gave informed consent before taking part to the study.

Paradigm. Participants sat on opposite sides of a desk divided by an occluding screen (Figure 1a), each given a separate LCD monitor, keyboard and mouse. All devices were controlled by the same computer (Dell OptiPlex 9020). All trials consisted of two stages: a private perceptual decision followed by a social exchange. During the private perceptual decision, participants performed a dot-count decision task with confidence ratings (32): Two boxes containing dots arrayed on a 20×20 grid in random order were briefly (160 ms) flashed on each participant's screen to the left and right of a central fixation cross. On each trial, one box contained $200 + d$ dots and the other $200 - d$ dots. Participants had to indicate which box contained most dots. Task difficulty was controlled by changing the d parameter and titrated to each participant independently so to reach an accuracy of around 70% (2-down 1-up procedure (35)). This ensured that independent of their individual sensitivity to the task, both experienced an equal amount of correct and error trials. Notice that, given the double staircase procedure, different dot displays were presented to the two dyad members on each trial, but the box with most dots (i.e., the correct answer) was the same for the two participants on any given trial. Thus, social information coming from the other person carried meaningful information.

Each dyad member indicated their independent response by mouse-click on a semi-continuous post-decision wagering scale (36), ranging from "100% sure LEFT" to "100% sure RIGHT", with the middle level removed to force participants commit to one or other decision. The scale had fifty levels per side. Participants were informed that each level of the scale corresponded to one token, which was awarded if the answer was correct and subtracted from their total score if the answer provided was wrong. Each token was worth £0.01, given to participants as cumulative earnings at the end of the experiment. Post-decision wagering scales are known to be dependent on the pay-off matrix used (37), which produces confounds if participants are too risk-seeking (38). As a control, participants were tested for loss aversion using the coin gamble task (39) and shown to be significantly loss averse (see Supplementary Information). Furthermore, we replicated the results in Experiment 2 and 3 using different confidence scale and instructions, to avoid the limitations affecting the use of post-decision wagering scales (38). Unless stated otherwise, all reported key Experiment 1 effects were replicated in Experiments 2 and 3 (complete results in Supplementary Information).

The member who responded first waited until the second had input their response. As soon as both members confirmed their answer by pressing space bar, the social exchange stage started, where each dyad member was informed about their partner's opinion. At this point, confidence changes were recorded continuously. In contrast to the standard judge-

Fig. 1. (a) Participants sat on opposite sides of a wooden occluder and use one monitor, one keyboard and one mouse each, controlled by the same computer. **(b)** After performing a perceptual judgment independently, participants saw on their own scale their partner's initial opinion (Static condition) or their partner's evolving opinion (Dynamic condition). They received feedback on their accuracy and earnings (not shown) at the end of the trial. Bidirectional black arrows represent real-time movement along the scale. The scale used in the actual task had 50 levels per interval.

adviser system paradigm (5), where confidence updates happen in discrete steps, here we recorded confidence judgments as they evolved over time: The mouse x-position along the scale was recorded every 200 ms and each data point so collected was treated as an individual post-decisional bet, contributing to the total amount of tokens participants were supposed to maximise. This was done to incentivise participants to update their cursor position along the scale as soon as their internal confidence changed. No clicking nor confirmation were required during the social stage to facilitate reliable and continuous tracking of confidence change. This stage expired after five seconds (26 data points). At this point feedback was provided to both members about the tokens earned by each member, and then a new trial began.

Manipulation. Our manipulation concerned only the social exchange stage. Two conditions alternated across blocks. In the Static condition, the choice and confidence level selected by each dyad member in the private phase appeared on their partner's scale as a static coloured cursor. Dyad members were at this point asked to continuously monitor and update their confidence by moving their mouse along the scale. In the Dynamic condition, the social exchange part started exactly as in the Static one, with each dyad member's cursor appearing on their partner's scale. However, and for the whole duration of the social part (five seconds), if a member updated their confidence, this would instantly appear also on their partner's scale and vice-versa. This led to a situation where participants were not only informed of their partner's original opinions, but also how those opinions changed in real-time as a function of their own updates (Figure 1b). The experiment began with three blocks of practice of 10 trials each (practice with the perceptual task alone, then in-

cluding the social exchange stage separately with static or dynamic interaction) followed by 14 experimental blocks of 25 trials each. Each experimental block contained 2 null trials randomly interleaved, which were private decision only trials, included so that participants were motivated to report their confidence accurately also during the private decision. In null trials, earnings were calculated from the confidence expressed during the private phase only. All other trials' earnings were computed instead from the social part. Analyses were performed to assess how social exchange (interactive or static) affected dependent variables of interest: confidence, accuracy and confidence-to-accuracy calibration. Data and analyses are available via OSF, https://osf.io/7b6py/?view_only=793327d07511448fa58e5b757aa6a46a

Results

Confidence changes asymmetrically for consensus and condition. The use of continuous post-decision wagering gave us a time series of confidence positions for both dyad members on every trial over the five seconds time window of each trial's social part. During the social stage, participants updated their confidence over a protracted period, with the largest changes occurring about one second after first exposure to their partner's opinion (Figure 2a). Further analysis indicated that confidence updates were typically a single, unidirectional transition (towards increased confidence when partners agreed and reduced confidence when they disagreed). Thus, when we counted trial-wise transitions — defined as the number of times during a trial's social stage that confidence changed from time-step t to $t + 1$, having remained static on the previous time-step (i.e., from $t - 1$ to t)

— we found that the number of update transitions within a trial significantly differed between conditions, but the effect size was small (average number of transitions: Static = 1.11, Dynamic = 1.18, $t(47) = 2.95, p = .004, d = 0.12$) indicating that marginally (but consistently) more updates happened during the Dynamic condition. As the average trial consisted of a single transition, analyses on confidence reported below are performed on last confidence points registered on each trial, unless explicitly specified.

The influence that social information has on each dyad member can be quantified as the distance between their post-exchange confidence and pre-exchange confidence: $\delta_C = C_{post} - C_{pre}$, with larger absolute values corresponding to greater impact of social information. The sign of δ_C is expected to be positive in agreement trials, when participants typically increase their confidence, and negative in disagreement trials, when they typically decrease their confidence. A 2x2 ANOVA on confidence change (Figure 2b) with factors of consensus with respect to the initial, private decisions (disagreement vs. agreement) and condition (Static vs. Dynamic) revealed significant main effects of both consensus ($F(1, 47) = 150.26, p < .001, \eta_G^2 = .7$) and condition ($F(1, 47) = 9.40, p < .01, \eta_G^2 = .005$), but no significant interaction ($F < 1$). As expected, average δ_C was negative in disagreement and positive in agreement (Figure 2c). The main effect of condition indicated that participants' final level of confidence was greater in the Dynamic condition than in the Static condition, with separate paired t-tests confirming this effect held regardless of consensus: Participants increased their confidence more when in agreement ($t(47) = 2.69, p = .009$) and decreased their confidence less when in disagreement ($t(47) = 2.08, p = .04$), in Dynamic compared to Static blocks. The results indicate that opinion change is dominated by the information content conveyed (i.e., agreement vs. disagreement), with the nature of interaction (static vs. dynamic) modulating rather than fundamentally altering this pattern. Nevertheless, the observed increase in confidence in the dynamic case (averaging 1.0 points on the scale) is non-trivial, for example, when considered in some parts of the opinion space (Figure 3) and when considering that it represents an average including trials when participants did not change their confidence at all (Figures 2c and 4b).

Figure 2c shows the density distribution of confidence changes divided by consensus (agreement vs. disagreement). Both agreement and disagreement distributions peaked around zero, which was by far the most common change (note that the y-axis in panel C uses a square root scale), indicating that very often participants ignored social information. Also of note is that on some disagreement trials participants actually increased their confidence, and agreement trials they decreased it. This is a surprising result if we consider that, from a normative (e.g., Bayesian) perspective, disagreement with an independent observer should always lead to reduction of confidence and agreement should always lead to an increase of confidence (if we assume that the participant believes that their partner performs better than

chance).

Fig. 2. (a) Average difference between confidence at time t and $t-1$ across trials and for each condition. x-axis represents the duration of a single trial's time window during which confidence update was possible. **(b)** Average confidence change in agreement and disagreement trials, plotted for each condition. **(c)** Confidence change density distribution in agreement and disagreement. **(d)** Toy model emulating how confidence can increase in a Dynamic disagreement trial. In a Static condition, the agents update their initial opinion with their discounted partner's opinion (dashed lines). In Dynamic interaction, the same update rule is applied on every iteration until equilibrium is reached (solid lines).

To explore this surprising pattern of confidence change more formally, a two-way repeated measures ANOVA was computed on the probability of an irrational confidence change, defined as confidence decreases in cases of agreement and confidence increases in cases of disagreement, again with factors of consensus and condition. To avoid including trials where increases/decreases in confidence were simply due to involuntary cursor movements (a "trembling hand"), we defined a confidence "change" as a shift larger than 5 confidence points in the unexpected direction. The findings were, however, consistent across cut-offs greater than zero. Results show a significant effect of consensus ($F(1, 47) = 7.88, p = .007, \eta_G^2 = .07$) but not of condition ($F(1, 47) = 2.56, p = .11, \eta_G^2 = .001$) and a significant interaction between the two ($F(1, 47) = 9.90, p = .002, \eta_G^2 = .005$), indicating that irrational confidence changes were more frequent in disagreement than agreement (0.018 vs. 0.004 of trials) and that the Dynamic condition produced more frequent irrational confidence increases than the Static condition (0.020 vs. 0.015 of trials, $t(47) = 2.59, p = .01$), as well as numerically fewer irrational confidence decreases (0.003 vs. 0.005 of trials, $t(47) = 1.98, p = .05$). The interaction between condition and consensus was however not replicated in Experiment 2 (Supplementary Information), indicating that the result was not robust to changes in the use of the confidence scale.

Although not normatively prescribed (e.g., in a Bayesian framework), opinion aggregation strategies described in the literature (3, 40, 41) can explain irrational decreases in confidence in cases of agreement. For example, averaging of

confidence would lead to this outcome when a partner agrees but is much less confident than the participant, such that the participant concludes that they should not have been so confident in the first place. Of more interest, therefore, are irrational increases in confidence after disagreement, which occurred more frequently than irrational decreases but which are difficult to reconcile with any obvious confidence-update strategy. Notably, this irrationality could occur through non-linear dynamics introduced by real-time interaction, as explored in a simple simulation of belief update in the two conditions. Consider an example trial in which a participant (P_{max}) starts off on a confidence level of $C_{max}^{pre} = 0.6(a.u.)$ while their partner (P_{min}) weakly disagrees ($C_{min}^{pre} = -0.4(a.u.)$). Suppose next that both participants use a simple update strategy, namely summing their own initial confidence with their partner's weighted confidence (here: weight = 0.80). This strategy has been shown elsewhere to be a good approximation of confidence change in joint decisions (40). In a situation where no interaction is allowed, participants can only use their partner's initial opinion to get to a new confidence, thus reaching levels of $C_{max}^{post} = 0.28$ and $C_{min}^{post} = 0.08$. However, a different outcome is observed in the interactive scenario in which the participant has access at each iteration to the partner's current confidence level and uses it to recursively updates his/her initial confidence. Figure 2d shows that this simple strategy leads to an oscillatory update that stabilises for P_{max} on a higher confidence than initially held. The effect reflects the fact that if P_{min} crosses the decision boundary 0, disagreement turns into agreement, thus supporting P_{max} 's initial opinion, instead of providing contradictory evidence, and therefore leads to an increase in confidence despite initial disagreement.

To test for recursive dynamics in our behavioural data we counted, for each condition, the average number of vacillations in a trial, namely the number of times the direction of the update (i.e., stationary/increase/decrease) changed in the update window. Formally: $V_i = (r_t - r_{t-1}) \neq 0$, with $r = \text{sign}(C_t - C_{t-1})$, for each trial i . Across participants, the average number of vacillations in a trial was significantly more frequent in the Dynamic than Static condition, providing some support for the intuition behind our simple model, although the effect was a small one (Static = 2.41 ± 1.26 , Dynamic = 2.55 ± 1.27 , $t(47) = 2.62$, $p = .01$, $d = 0.11$). In this way, irrational increases in confidence in cases of disagreement could arise if participants updated their judgments based on the observed updates of their partner (which in turn are influenced by their own judgment), thus treating these updates as if they were independent evidence. A prediction arising from this simulation is that confidence increases in disagreement should only be observed for the participant expressing higher confidence in their judgment on the trial (the dominant individual). Indeed, participants showed a significantly higher rate of irrational increases in the Dynamic condition compared to a Static condition when they were the more confident of the partners on the trial (0.012 vs. 0.008 of disagreement trials, $t(47) = 3.29$, $p = .001$, $d = .21$), and not

when less confident (0.007 vs. 0.007 of disagreement trials, $p > .8$).

Dyadic interactions in opinion space. The preceding analyses explore opinion change when the data are aggregated across broad categories (e.g., agreement vs. disagreement trials). To explore more nuanced behaviour as a function of participants' absolute and relative levels of confidence, we explored our data as a function of a 2-dimensional "opinion space" (40) as shown in Figure 3. The figure plots confidence change following interaction within this space. Here, the x-axis value indicates the confidence of whichever participant in the dyad is the more confident on any given trial in the private judgment phase, henceforth the "dominant" member (P_{max}) on the trial, thus ranging from 1 (minimum confidence) to 50 (maximum confidence). The y-axis value gives the confidence of the less confident, or "dominated", member of the dyad in their initial judgment on the trial (P_{min}), on a scale ranging from -50 (disagreement with maximum confidence) to 50 (agreement with maximum confidence). This plot creates a grid of possible social situations in which the dyad's state - both members' choices and their confidence - is fully represented by (x,y) coordinates, while collapsing across the particular side of participants' choices (left vs. right box). In Figure 3, pixel colour indicates the median change in confidence from pre- to post-exchange of the dominant (upper panels) and dominated (lower panels) member of the dyad on each trial. The dominant and dominated participants' confidence change can be combined into a single vector field (Figure S1) visualizing dyadic transitions in opinion space (40). Real-time animations of confidence transition in opinion space for each condition can be found at https://osf.io/7b6py/?view_only=793327d07511448fa58e5b757aa6a46a.

Figure 3 shows once again the overall increase in confidence seen in dynamic vs. static interactions, with dynamic interaction characterised by greater increases in confidence when partners agreed (cf. larger red area in upper half of Figure 3b than 3a) and smaller decreases when they disagreed (cf. smaller blue area in lower half of Figure 3b than 3a). The contrast plots (Figure 3c and 3f) more precisely identify the locus of these between-condition differences, while also highlighting the magnitude of the effects in certain conditions. Thus, dynamic interaction leads to particularly marked confidence increases when partners began the social stage in agreement but with low confidence (points marked x in Figure 3). Confidence change in the Dynamic condition (panel b,e) in these conditions of uncertain agreement is 20-30 confidence points, and ~ 15 points greater than in static interaction blocks: Thus, when interacting dynamically, but not statically, two uncertain partners tended to reinforce each other's opinion so that together they converged on the maximum possible confidence level. The other key point of interest in the contrast plots lies in the disagreement half of the opinion space, specifically at the points labelled y in Figure 3c and 3f. These were trials in which the dominant member was highly confident and the dominated mem-

Fig. 3. Confidence change observed for every social situation, according to the confidence of the more (P_{max}) and less (P_{min}) confident participant. (x,y) coordinates represent the pre-exchange dyad state, while the colour (z-axis), represents confidence change. Panels a-c represent confidence change in dominant trials in Static condition, Dynamic condition and their contrast respectively. Panels d-f represent confidence change in dominated trials in Static condition, Dynamic condition and their contrast respectively. Panels c and f represent contrasts between the two conditions (contrasts b-a and e-d respectively). Trials within each condition and dyad were linearly interpolated, due to data sparseness.

ber weakly disagreed, a situation described in our simple simulation above: The warmer colour at y in Figure 3c indicates that disagreement had markedly less impact on the dominant partner's confidence when the dyad interacted dynamically rather than statically. The corresponding point in Figure 3f indicates that, similarly, larger shifts in the dominated participant's confidence toward the dominant individual's position were observed in Dynamic compared to Static blocks. Overall, therefore, this opinion space analysis identifies the conditions under which dynamic interaction has its largest impact—when partners agree with symmetric low levels of confidence, and when they disagree with asymmetric levels of confidence—and shows that this impact is substantial in these conditions.

Comparing confidence updates with Bayesian aggregation.

We next compared participants' confidence changes in interaction with a normative Bayesian strategy. For this analysis, we treated confidence ratings as subjectively estimated probabilities that a particular decision is correct (42–44), while applying a linear transformation to prevent values of 0 and 1 and thus avoid impossible solutions: range of 0.01 = "100% Sure LEFT" to 0.99 = "100% Sure RIGHT". The probabilities p_s and p_p so obtained—representing dyad members' independent priors on RIGHT being correct (cf. 45)—can now be integrated into the normative posterior:

$$post_{norm} = \frac{p_s p_p}{p_s p_p + \neg p_s \neg p_p} \quad (1)$$

where $\neg p_s$ and $\neg p_p$ are $1 - p_s$ and $1 - p_p$ respectively, representing the subjective prior probability on LEFT. The resulting posterior confidence represents the post-exchange confidence held by a normative opinion aggregation method on RIGHT being the correct answer. The normative model reproduces some patterns of opinion change observed in empirical dyads (40).

Figure 4a plots the difference, Res , between the normatively prescribed confidence change, δ_{norm} , and the empirically observed value, δ_{emp} , as a function of consensus and interaction condition. A 2x2 ANOVA on participants' mean Res values revealed a significant effect of consensus ($F(1, 47) = 68.37, p < .001, \eta_G^2 = 0.46$) and interaction condition ($F(1, 47) = 4.97, p = .03, \eta_G^2 = .002$) but no significant interaction ($F < 1$). Participants were more confident than prescribed by Bayesian updating in disagreement for both conditions ($t(47) > 8.34, p < .001$), and less confident in agreement, significantly so in Static blocks ($t(47) = -3.06, p = .003$) but not in Dynamic blocks ($t = -1.56, p > .1$). These findings indicate that participants systematically underweighted their partner's advice, but did so particularly strongly when they disagreed, thus replicating previously observed decision biases of egocentric discounting and confirmation bias that affect the perception of social information (10, 19, 46). The main effect of interaction condition mirrored the overall effect of dynamic interaction leading to increased confidence, thus increasing the discrepancy from optimal updating in case of disagreement, but reducing it in case of agreement.

Bayes theorem can also be used to infer the participants' perception of the social information. Equation 1 is used by the optimal observer to infer the predicted posterior confidence given a prior confidence level p_s and a partner's opinion p_p . However, by solving the equation for p_p (i.e., the likelihood term), we can infer the *perceived* partner's confidence $\hat{p}_p$, given the degree to which the participant updated their confidence from their initial judgment (the prior, p_s) to a final decision following social interaction (the posterior, $post_s$):

$$\hat{p}_p = \frac{post_s(p_s - 1)}{2p_s post_s - p_s - post_s}; \quad (2)$$

In this way we can quantify the weight that participants assigned to their partner's judgement across trials, contrasted with the weight (i.e., probability correct) that the partner themselves conveyed in their confidence judgments. Comparing the distribution of these values across trials reveals how objective social information (i.e., partner's stated support for the participant's opinion) becomes distorted when perceived and acted on by the participant (i.e., actual use of partner's social information). As shown in Figure 4b, whereas partners' stated confidence ratings were fairly evenly distributed in terms of conveying social information ranging from maximal disagreement (0 on the x-axis) to maximal agreement (1), the weight that participants assigned to their partners views showed almost categorical behaviour, with separate peaks at $\hat{p}_p \sim 0.5$ (i.e., advice treated as carrying little or no information) and $\hat{p}_p \sim 1.0$ (i.e., advice treated

Fig. 4. (a) Difference *Res* between observed confidence change and normatively prescribed confidence change. **(b)** Contrast between partner's stated support for the participant's independent view (objective social evidence) and the participant's perceived support of the partner's opinion (perceived social evidence), as inferred using inverted Bayes. The plots show density distributions calculated with a Gaussian kernel method (bandwidth=0.04). A value of 1 (a value of 0) corresponds to social information that maximally agrees (disagrees) with one's initially expressed opinion.

as objectively correct) (47). Further analysis (Supplementary Analysis) confirmed that in both interactions conditions, and both when holding the dominant or dominated view, participants tended to use partner's objectively stated opinion in a self-serving manner, thus overplaying the support that social information provided for one's own initial judgment. To formally test for this distortion, agreement trials (i.e., x-axis greater than 0.50) were divided into six bins of evidence, and a linear model with a linear and quadratic terms was fitted: $frequency = \beta_0 + \beta_1 evidence + \beta_2 evidence^2$. Results showed that the quadratic terms was not significant for partner's stated evidence (dominant: $\beta_2 = 0.50, SE = 0.21$; dominated: $\beta_2 = 0.22, SE = 0.46$), but was significant for the participant's perceived evidence (dominant: $\beta_2 = 2.39, SE = 0.57, t = 4.19, p = .02$; dominated: $\beta_2 = 3.84, SE = 0.56, t = 6.75, p = .006$), explaining 80% and 90% of the variance for dominant and dominated trials respectively (*AdjustedR*²). The result is evidence of the fact that participants tended to treat advice bimodally as either

highly supportive of their own initial opinion or as carrying little informational value.

Coupling of confidence changes during interaction. The analyses above consider opinion change for each dyad member separately. To investigate how the magnitude of partners' opinion changes co-varied across trials, we calculated across-trial correlations of absolute confidence change, $|\delta C|$, for members of each dyad. Pearson's *r* coefficients were calculated for each dyad as a function of dyadic consensus (agree vs. disagree) and interaction condition (dynamic vs. static). A 2x2 ANOVA on the resulting values across dyads (Figure 5) revealed a main effect of consensus ($F(1, 22) = 20.93, p < .001$) but not of condition ($F(1, 22) = 1.71, p = .20$), and a significant interaction between the two ($F(1, 22) = 38.39, p < .001$). When dyad members did not see each other's confidence changes in the social exchange stage (Static condition), confidence changes did not correlate significantly between partners ($h_1 = r > 0, t(22) < 1.28, p > .2, d = 0.26$). This finding is not unexpected, but nor is it trivial—for example, a positive correlation might be expected in agreement trials as a consequence of a boost to both participants' confidence when they agreed but were initially uncertain, such that agreement led to increased confidence for both. This did not seem to occur. In contrast, in the Dynamic condition, partners' confidence changes became coupled: In agreement trials, the correlation was positive, indicating that the more one member increased their confidence, the more their partner also increased their confidence. In disagreement, the correlation was negative, indicating that the more one member decreased their confidence in their initial decision, the less the partner decreased theirs. Pairwise contrasts showed that, compared to Static condition, in the Dynamic condition correlation coefficients were significantly greater for agreement ($t(22) = 4.89, p < .001, d = 1.20$) and somewhat smaller for disagreement ($t(22) = -2.02, p = .05, d = -0.52$). The negative correlation found in disagreement Dynamic trials, was replicated in Experiment 3, but not in Experiment 2 (Supplementary Information). Further analyses (Supplementary Information) showed that the effect could not be explained by participants using their partner's reaction times (i.e., "unwillingness to move") in the Dynamic but not in the Static condition. Coupling of confidence changes in interaction suggests that participants were influenced by their partner's confidence change when updating their own opinion, rather than basing their change solely on their partner's initial (independent) judgment as normatively prescribed.

Performance analysis. A tenet in the judgment aggregation literature is that social interaction hampers collective wisdom by breaking the independence of the individual judgments (48). The traditional interpretation of the wisdom of crowds (2, 49), named here the "noise cancelling hypothesis", explains the accuracy improvement observed in opinion aggregates as a statistical phenomenon where noise reduces after independent samples (here the private initial opinions) are averaged together. This hypothesis predicts that breaking the independence between measures should have negative ef-

Fig. 5. Effect of condition on the correlation between absolute confidence changes of the two participants across trials. Average Pearson's correlation coefficient is plotted as a function of consensus and condition. One dyad removed for a missing cell.

fects on accuracy, as errors become correlated instead of averaging out. In their experiment, Lorenz and colleagues (48) showed that simple exposure to others' opinions had damaging effects on aggregate accuracy. If the noise cancelling interpretation is correct, in the present study we should observe that (1) simple exposure to another person's opinion negatively affects performance; (2) the effect of social exposure is even more damaging on performance in the Dynamic condition, as this condition affects the independence of the individual estimates more than the Static one (Figure 5).

A 2-way ANOVA on accuracy with factors condition (Static vs. Dynamic) and decision stage (pre- vs. post-exchange) showed a significant effect of decision stage ($F(1,47) = 47.00, p < .001, \eta_G^2 = .16$) but no significant effect of condition ($F < 1$) nor a significant interaction ($F < 1$). Social information had a beneficial effect on average accuracy (pre-exchange accuracy = 0.72, post-exchange accuracy = 0.75). The finding indicates that, contrary to (48), exposure to another person's opinion did not reduce accuracy. Furthermore, Dynamic interaction did not reduce accuracy improvement compared to Static, indicating that increased dependence between confidence updates (as indicated in the analyses of Figure 5) had no significant damaging effect on accuracy (or accuracy improvement) either.

However, condition might have affected people's opinions without making them changing their initial answer (5). We thus tried to define a more nuanced definition of accuracy improvement as confidence changes toward or away the correct end of the scale: $\delta_{accG} = (C_{post} - C_{pre})^{Acc} * (C_{pre} - C_{post})^{1-Acc}$, where $Acc \in \{0, 1\}$. We tested whether participants improved their initial judgment although keeping their initial views. The same 2x2 ANOVA did not show any effect of condition on graded accuracy improvement δ_{accG} nor significant interaction ($F < 1$), thus rejecting the idea that condition had an influence on accuracy.

A third and final measure of performance considered was the calibration of confidence relatively to objective accuracy, defined here as the type II A_{ROC} (50). The same two-way ANOVA used for choice accuracy was run on type II A_{ROC} . Results show a significant effect of decision stage ($F(1,47) = 89.58, p < .001, \eta_G^2 = .25$), indicating calibration improvement from pre- to post-exchange phase (0.60 vs. 0.66), but no effect of condition nor interaction between the two ($F < 1$), further confirming that, overall, the nature of interaction (static vs. dynamic) did not impact on calibration or improvement thereof.

Discussion

The present study compared social exchange involving static, one-step communication with exchange characterised by dynamic and recursive interaction. We hypothesized that real-time bi-directional dynamics, which characterise many daily life interactions of social influence (22), would have systematic impact on decisions made in a social context, over and above the effects of the information brought by each individual to the interaction, as studied in traditional judge-advisor system experiments (5, 51). Across conditions with equal information available—because in both the Dynamic and Static conditions, dyad members viewed perceptual evidence separately and for 160 ms only—we observed different opinion aggregation strategies according to the nature of communication between partners. Specifically, dynamic interaction produced higher confidence changes in agreement and smaller confidence changes in disagreement by breaking the independence of dyad members' opinions: Confidence changes of the two participants became correlated during Dynamic interaction compared to a Static baseline so that, in agreement, greater increases in confidence for one member were associated with greater confidence increases for their partner, leading to belief escalation. In disagreement, greater changes in confidence for one member were associated with smaller changes in confidence for their partner, reducing the impact of disagreement on belief updating.

These combined results can be understood in terms of individuals making use of their partner's change in confidence to update their opinion, without taking into account that this change was biased (and indeed generated) by exposure to their own judgment. People are known to quickly reach decisions even when information is scarcely available by taking into account a host of circumstantial variables that are known to co-vary with problem-specific evidence, but that are not themselves strictly task-relevant (52–54). Interpreting someone's changes of mind as another cue for confidence is sensible in many daily life situations. Indeed, if somebody's beliefs are fickle, we have reasons to believe s/he must be uncertain. In the case of social interaction, however, this heuristic leads to potentially sub-optimal self-reinforcing dynamics, when a person uses the impact of his/her own opinion on the other person as evidence for the opinion itself. The impact of this circular reasoning was particularly marked in the case of two partners agreeing but with low or intermediate levels of confidence: In these cases, dyads often escalated together to-

wards maximal confidence in their shared judgement through dynamic interaction, an effect not observed when information exchange was static and limited to each individual's independent judgment.

Phenomena of belief escalation have already been observed in relation to sharing confidence judgments in group decisions (27, 55). These studies found that reciprocal social interaction can make people's judgments more risky and extreme, a result reminiscent of earlier findings on group polarisation (29). The present study shows that a crucial cause of confidence escalation is the use of redundant information: People should only use each other's independent opinions to arrive at a final decision, because this is the only information that carries task-relevant value. However, they also (incorrectly) use how much their own opinion is affecting their partners. This strategy creates dependencies that can potentially create unwanted non-linear dynamics. Beyond confidence escalation as described above, a more subtle but nevertheless consistent effect of this strategy in our data was that participants occasionally increased their confidence despite initially learning that their partner disagreed with them (a surprising irrationality that occurred more frequently than the mirror effect of decreasing their confidence when a partner agreed). Our analyses suggest that partner's changes of mind are sometimes perceived as supporting evidence for one's views: When a partner initially disagrees, but subsequently loses confidence in this view (or even reverses it) on learning the participant's view, it seems that the participant takes this as evidence in favour of their initial position, and therefore increase their confidence. This phenomenon cannot easily be explained by static aggregation rules like averaging, summing or Bayesian integration (3, 40, 41), but is predicted by a recursive update model.

Notwithstanding these differences in confidence updating across static vs. dynamic interactions, participants' overall accuracy showed a consistent benefit from social information exchange. The benefits of social exchange were of similar magnitude across static and dynamic interaction conditions, whether this benefit was measured in terms of overall accuracy, confidence in the correct answer, or the calibration between confidence and objective performance. This parity was observed despite different interaction dynamics across conditions, at least in part because these dynamics led to opposing effects on accuracy across trials. Thus, when we contrast participants' behaviour with a Bayes optimal strategy, we find that they consistently underweighted their partners' opinion and thus did not benefit optimally from social exchange. When comparing dynamic to static interaction, this underweighting relative to Bayes was greater in cases of disagreement and reduced in cases of agreement, for the reasons discussed above, resulting in little net difference in accuracy across conditions. An interesting issue for future is whether the introduction of systematic biases across members' initial judgments (e.g., 40) might generate greater errors in interaction than non-interaction, due to escalation of confidence in incorrect answers (56–58).

Although it is informative to compare empirically observed behaviour with an optimal model grounded in a probabilistic interpretation of confidence (45), participants clearly departed from the Bayesian strategy commonly explored in the opinion aggregation literature (41, 59, 60), in which opinions are combined in relation to expressed confidence. The use of inverse Bayes allowed us to compare the objective information conveyed from social partners with the information perceived by a participant. Results evidenced that social information was distorted by the receiver in a self-serving manner and asymmetrically for agreement and disagreement, in line with the advice-taking literature suggesting the presence of egocentric and confirmation biases (10, 46). More specifically, the weighting of partner's information (i.e., use of social information) seemed to follow a bimodal distribution, with peaks around 50%, corresponding to neutral social information, and 100%, corresponding to maximally supporting social information. These results are consistent with the hypothesis that people are solving a categorical inference problem (cf. 47): Instead of using continuous social information as it is provided by their social partners, participants seem to classify each trial as "partner is wrong" vs. "partner is correct" and, once this categorization is performed, use social information accordingly to update their views. Accordingly, participants would try to minimize situations of uncertainty (e.g. 0.25 or 0.75 evidence), thus maximizing the impact of social information on final confidence.

Our key experimental results were replicated using linear-mixed effects regressions and by running two further experiments, reported in the Supplementary Information material. The same paradigm used in Experiment 1 was extended with two aims: (a) to replicate the results found in the current experiment using a different method to report confidence, and (b) to make sure that the escalation effects found were not due to confounding factors. Indeed, a perhaps more parsimonious explanation of the interactive effects found is that participants quickly forgot the initial configuration and were only left with their current expressed opinions. This hypothesis can, for example, explain non-linear opinion reinforcement. We therefore included confidence anchors to remind each participant of the initial, independently expressed confidence in their own judgment (Experiment 2) and from their partner (Experiment 3). Replication of key findings across experiments—including confidence change asymmetry, update coupling, and confidence escalation—indicated that the results are robust to different instructions and different uses of the confidence scale. Collectively, these findings show that social influence depends not only the task-relevant information provided by social partners, but also on the modality in which information is shared and transformed across individuals. Real-time interaction, as seen in most daily social exchanges, is recursive and dynamic in nature, and thus an understanding of social decision making requires consideration of these phenomena.

Conclusion

In many daily life scenarios, information is collectively manipulated by several agents who interact in closed-loop recursive dynamic systems. Here we explored these dynamics in a controlled setting, using a simple perceptual decision task and computer interface for communication, to allow quantification of the impact of social exchange on individual decision making. We find that interaction dynamics affect individuals' decisions above and beyond the content of their shared information—the medium becomes (part of) the message. In the aggregate, the impact of interaction dynamics is subtle but consistent, evident as a general increase in confidence in decisions made. However, the impact is very marked in specific situations, notably when shared but uncertain beliefs become mutually reinforced to a state of near certainty, and when a decision maker interprets vacillation in a partner's weak disagreement as positive evidence for their views.

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