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Bayes Optimal Integration of Social and Endogenous Uncertainty in Numerosity Estimation

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Abstract

One of the most prominent social influences on human decision making is conformity, which is even more prominent when the perceptual information is ambiguous. The Bayes optimal solution to this problem entails weighting the relative reliability of cognitive information and perceptual signals in constructing the percept from self-sourced/endogenous and social sources, respectively. The current study investigated whether humans integrate the statistics (i.e., mean and variance) of endogenous perceptual and social information in a Bayes optimal way while estimating numerosities. Our results demonstrated adjustment of initial estimations toward group means only when group estimations were more reliable (or "certain"), compared to participants' endogenous metric uncertainty. Our results support Bayes optimal social conformity while also pointing to an implicit form of metacognition.

Keywords: Social conformity; Bayesian integration; Implicit metacognition; Numerical estimation

1. Introduction

Many aspects of human cognitive processing, including perceptual judgments, are subject to social influences (Sherif, 1935). One of the most common forms of such social influence on the human decision-making process is social conformity. Social conformity is often defined as matching one's beliefs, attitudes, and actions to the group's, even when the majority con-

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flicts with the self (Li, Li, & Li, 2019). Social conformity serves normative (to gain acceptance) and informative influence (to gain information) functions. Regarding the normative influence, participants conform to the group decisions even for the obvious perceptual decisions (e.g., line length judgment task) to gain group acceptance (Asch, 1955), which can be moderated by contextual factors (i.e., presence of objective accuracy; e.g., Wijenayake, van Berkel, Kostakos, & Goncalves, 2020), personality traits (e.g., Klein, 1967), and confidence (e.g., Deutsch & Gerard, 1955).

The informative influence of social conformity is related to information seeking (Deutsch & Gerard, 1955), which comes into play particularly when the agent has a higher uncertainty regarding the decision to be made. For instance, Wijenayake et al. (2020) observed stronger social conformity when participants reported low confidence in their initial responses (see also Park, Goïame, O'Connor, & Dreher, 2017). Parallel to these results, Cross, Brown, Morgan, and Laland (2017) demonstrated that participants updated their initial response in a way that conformed to the group response when they were unsure about the accuracy of their original responses, which was referred to as the "copy when uncertain" pattern by Toelch, Bruce, Newson, Richerson, and Reader (2014; see also Toelch et al., 2009).

Other studies point to the importance of group decision statistics (i.e., the mean and variability of the group decisions). For instance, Rosenberg (1963) showed that the perceived accuracy of others predicts conformity, while Li et al. (2019) demonstrated that social conformity is reduced by decreasing group reliability, compared to the agents' endogenous information. People indeed conform to others' advice according to their confidence in decisions (instead of the task difficulty), suggesting optimal advice-taking as metacognitive ability increases (Pescetelli, Hauperich, & Yeung, 2021).

Overall, these findings emphasize the interaction of endogenous and social factors in determining conformity. This view corroborates the premises of the Bayesian information integration, which entails weighing endogenous and social information according to their relative reliability (Toelch & Dolan, 2015; see also: Bond, 2005). Accordingly, how much the agent weighs endogenous versus social information determines the degree to which the resultant judgments approach Bayes optimality. Accordingly, a Bayes optimal agent should weigh/credit social information more heavily than endogenous information when the agent is uncertain of the correct answer. Given that such a comparison of the relative reliability of the two sources does not necessitate an explicit verbalization of cognitive states, this judgment entails an implicit form of metacognitive awareness (Yon & Frith, 2021). Thus, the relative weighing of the social source can index the level of subjective confidence regarding the accuracy of the decisions, which is widely used as an explicit measure of metacognition (Fleming & Lau, 2014).

Along with the studies above, Bahrami, Didino, Frith, Butterworth, and Rees (2013) demonstrated that humans take into account others' subjective confidence reports in perceptual decision tasks to maximize accuracy. This finding suggests that metacognitive processes can help optimize perceptual decisions when communicated explicitly. However, Bahrami et al.'s (2013) findings do not readily generalize to the estimation performance, which has been addressed by Molleman et al. (2020). They investigated whether social information is integrated in a Bayes optimal way by asking participants to estimate the number of

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animals presented on the screen using a continuous sliding scale. After their first estimation, participants were shown estimations from three pre-tested participants on a sliding scale and asked to make a second estimation on the same sliding scale. The mean of the "social" estimations was determined as deviating 20% from the first estimate of the participant, and the variance was determined as 10 or 100 according to the experimental conditions. Molleman and colleagues' participants weighed social and endogenous information in a Bayes optimal way (i.e., increased the weight linearly according to the source reliability) while making a second estimation.

As the goal of Molleman et al. (2020) was to investigate the dynamics of social conformity given the relative group estimation statistics (i.e., the mean and variability), the appropriate use of second estimations on a sliding scale along with the social estimations might have rendered the amount of social deviation (i.e., within-group deviation of the social values and deviation between the social and the participants' estimations) too obvious based on the exact locations of the estimations on a horizontal line (with a visually obvious depiction of deviation metrics). This methodological approach to investigate these dynamics would allow the involvement of explicit strategies such as deliberate matching or unmatching of the estimations to the social information. Given this methodological detail, the second estimations of Molleman et al. (2020) could have resulted from visual-perceptual inference without necessitating any magnitude-based implicit calculation (i.e., performing mental calculation of estimation statistics implicitly) of the estimation statistics (i.e., mean and variability). Accordingly, Molleman et al. (2020) methodological approach did not directly reveal whether participants can (a) keep track of their estimation parameters, (b) implicitly calculate social estimation parameters, and (c) make an implicit comparison between the two. Thus, how the integration of endogenous and social information can reflect metacognitive processes needs further investigation. Investigating such an implicit comparison is crucial to hint at implicit metacognitive abilities as reflected in conformity in a Bayes optimal way. One simple alternative approach is reporting the numerosity estimations by directly typing in the absence of visual cues that hint at the relative deviance of the estimation.

The current study tested whether participants updated their initial responses according to the relative certainty of group responses with respect to participants' own (i.e., Bayesian integration.) Accordingly, a Bayes optimal agent should integrate these two sources of information according to their relative certainty (i.e., reliability) such that a more certain source of information should take higher weight in the ultimate decision-making process. Thus, if participants are Bayes optimal information integrators, their response updates should be predicted by the weighted average of the self-made (i.e., endogenous information) and group estimations (i.e., social information) where weight is inversely proportional to the uncertainty in the corresponding sources. Accordingly, we hypothesized that the response updates should depend on the weighted average of endogenous and social information. Similarly, we hypothesized that social conformity would increase with decreasing uncertainty (i.e., as indexed with the coefficient of variation [CV] of the group estimations, where higher values indicate lower uncertainty) of the group's estimation with respect to the participants' own uncertainty. Such a behavioral pattern would point to an implicit form of metacognition as it does not

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require explicit reports of self-confidence, which is one of the primary operationalizations of metacognitive monitoring (e.g., Fleming et al., 2014).

The current study introduces several critical methodological advantages that aim to advance upon the pioneering results obtained by Molleman et al. (2020). First, instead of keeping the variance of the social estimations constant, we adjusted the level of this critical experimental factor per participant based on the variance in their earlier performance in the same task. This way, we precisely controlled for the relative uncertainty in participants' and social group's uncertainty (the use of variance as a proxy for uncertainty is widely documented—e.g., Cheng, Shettleworth, Huttenlocher, & Rieser, 2007; De Corte & Matell 2016a, 2016b; Gür, Duyan, & Balcı, 2021). Furthermore, the source of social information in our study did not allow participants to use any auxiliary visuo-perceptual information (cf. presenting deviance of one's estimates from those of the group on a line) to estimate the metrics of social uncertainty (i.e., that is associated with the variability of group estimations). This alternative methodological approach aimed to reveal whether the potential Bayesian integration can be achieved via the implicit calculation of estimation statistics. Given these methodological modifications, the current study aims to (a) test the generalizability of Molleman et al.'s (2020) original results with a different methodological approach and (b) add further theoretical advances that can potentially reveal the characteristics of implicit metacognitive processes during social conformity. Finally, our participants were not asked to provide an explicit judgment of confidence to increase the ecological validity of our paradigm.

2. Method

2.1. Participants

Forty-seven undergraduate students from Koç University (İstanbul, Türkiye) participated in this study. Data from eight were discarded from the formal analyses due to unreasonable second-chance responses (i.e., exceeding the estimation beyond the range of three times larger than the maximum numerosity or below the upper limits of the subitizing range). As a result, data from 39 participants were included in the formal analyses (32 female, one did not report gender, $M_{\text{age (years)}} = 20.5$ (± 1.54), one did not report age, 33 right-handed, and three did not report handedness). Participants received one extra course credit in return for their participation. All participants provided an informed consent form upon their participation in the study. This study was approved by the Koç University Institutional Review Board (IRB, protocol number: 2020.113.IRB3.053).

2.2. Stimuli and apparatus

The stimuli were dot arrays in a visual circular area that were controlled for their convex hull, dot density, and average diameter, which were created using a program that was written by Gebuis and Reynvoet (2011). There were 13 (from 12 to 24) target numerosities each with 18 different configurations, where each configurations were presented with equal probability.

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The experiment was conducted in the Pavlovia online experiment platform (Bridges, Pitiot, MacAskill, & Peirce, 2020), and all stimulus sizes were adapted to the participants' monitor.

2.3. Procedure

The experiment consisted of two parts of a numerical estimation task with the details below.

2.3.1. Baseline block

In the baseline block, participants were shown the target dot arrays with a target numerosity for 300 ms. Participants were asked to estimate the number of dots in the stimulus that they were presented with (baseline estimations) by typing their estimations on the keyboard. Participants did not receive any feedback regarding their estimations. The baseline block contained 104 trials where the participants estimated each target numerosity eight times. Upon completion of the baseline block, these baseline estimations' mean and standard deviation were calculated according to the target normalized estimations (where target normalized estimation = estimated numerosity/target numerosity). At the end of the baseline block, the CV of the target normalized estimations was calculated as follows:

$$CV_{\text{target normalized estimations}} = SD_{\text{target normalized estimations}} / M_{\text{target normalized estimations}}, \quad (1)$$

where *SD* stands for "standard deviation," and *M* stands for "mean."

The main purpose of the baseline block was to quantify the accuracy and the level of endogenous uncertainty in numerical estimations. These estimates were then used to determine the relative bias with respect to the target numerosity (i.e., under or over the target numerosity and its magnitude) and the relative reliability of the social information in the social block. We did not analyze the raw estimations from the baseline block.

2.3.2. Social block

Participants were told that, as in the baseline block, they would estimate the number of dots in a dot array that they were shown. Different from the baseline block, participants were told that they would also see the estimation of five different individuals for the given trial. Thus, as in the baseline block, in the social block, participants were first presented with the target numerosity for 300 ms and were asked to estimate the number of dots in the stimulus that they were presented with by typing on the keyboard. After their estimation, participants were demonstrated with five different estimations from mock participants that they believed to have completed the experiment before. Participants were instructed that they could change their initial estimate if they wanted to (second-chance responses). Participants were instructed to enter the same estimate if they did not want to change their original estimate. Each mock participant was represented with different polygons under which the estimates were presented (located horizontally on the screen) until a second-chance response was recorded. Participants were not provided with feedback regarding their estimation performance.

Uncertainty emerges due to the variability of incoming data, which can be statistically captured by variance or entropy. We chose variance as the measure of uncertainty, particularly given the nature of the underlying distribution of social estimates in our experimental setting

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(unimodally distributed). The estimates of the mock participants (will be referred to as "social estimations" hereafter) were randomly drawn from a Gaussian distribution with a mean and standard deviation determined according to 3 (higher, same as or lower mean than the mean of baseline estimations) × 3 (higher, same as or lower CV than the CV of baseline estimations) experimental conditions. This manipulation made it possible to investigate how the bias and variability of social estimations altered the second-chance responses of the participants. As a result, participants completed a total of nine social blocks and a baseline block in total. A 1-min-long break separated each block.

Each experimental condition was tested throughout the block composed of 52 trials. As a result, participants completed 9 × 52 (plus 104 trials in the baseline block) = 468 trials in total. For the social estimations, higher and lower mean and CV conditions were determined as ±10% of the mean and CV of the target normalized estimations (i.e., estimated numerosity/target numerosity) in the baseline block. For example, if the mean target normalized estimations in the baseline condition was 1, the mean of target normalized social estimations for higher and lower mean conditions were 1.1 and 0.9, respectively. The task took around 40 min to complete. Fig. 1a depicts one trial in the experimental condition. All the materials, code, and data used in this study are available in the Open Science Framework (OSF; https://osf.io/7nvxc/?view_only=f32454e46c694cf98f26845bd599a2ae). This study was not preregistered.

3. Analytical approach

Before data analysis, we performed listwise deletion to all first and second estimates that were below six or above 36 (i.e., half below the minimum numerosity and half above the maximum numerosity). This deletion resulted in 2.86% of the whole dataset being discarded from the main analysis (13.4 trials per participant on average). We then normalized the baseline estimations and the social estimations with the target numerosity. Following this normalization, we calculated the weighted average of the endogenous and social estimations based on the first estimations in the social block. To this end, we calculated the posterior estimations (Est_{post}) by weighting the first estimations in the social block with the social estimation precisions (i.e., inversely proportional CV of the social estimations) using the following equation:

$$\begin{aligned} Est_{post} = &(Est_{self} \times CV_{social}/(CV_{social} + CV_{self})) \\ &+ (Est_{social} \times CV_{self}/(CV_{social} + CV_{self}))' \end{aligned} \tag{2}$$

where Est_{self} and Est_{social} stand for the target normalized estimations of the participant (own estimation) and groups' (social estimation) in a given trial, respectively. In Eq. 2, the CV refers to the estimation precision (i.e., overall, how precisely the numerosities are estimated, where low CV indicates high estimation precision). Thus, in this equation, the estimations with lower precision (i.e., higher CV) will result in the attribution of more weight to the other source of information. For example, if the participants' estimation precision is lower than the group's in a given trial, the higher values CV_{self} will be multiplied by Est_{social}, assigning it a higher weight. Conversely, if the participants' estimation precision is higher (i.e.,

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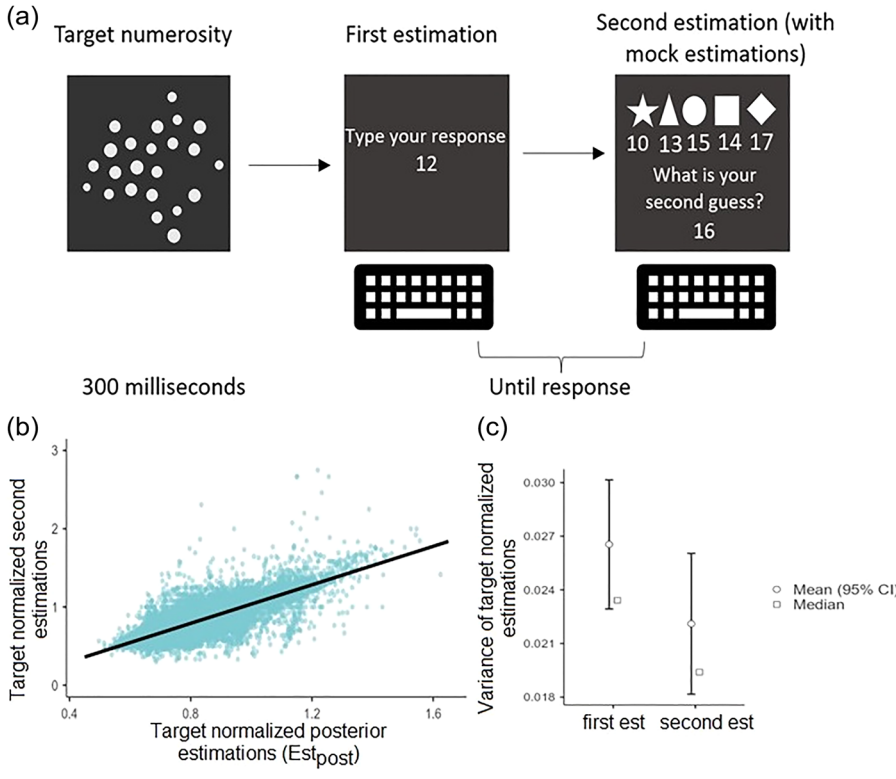


Fig. 1. (a) Graphical illustration of one example trial in the experimental condition. Participants are first demonstrated with the target numerosity and then asked to estimate the number of dots the stimulus included. Finally, participants are shown five different social estimations and are given a second chance to update their estimations. (b) The linear relationship between posterior estimations and target normalized second estimations. (c) The comparison between target normalized first and second estimation variances.

lower CV_{self}), compared to that of the group's, the weight of the group's estimate will be lower, resulting in the higher weighting of Est_{self}. This equation allows information integration according to its reliability based on Bayesian logic.

Both CV_{self} and CV_{social} values in Eq. 1 were calculated on the basis of the target normalized estimation statistics. To test our hypothesis (i.e., if response updating is Bayes optimal, second estimates should be a linear function of Est_{post}) in a single model, we conducted a linear mixed effects model as depicted below:

Model 1: Second estimates $\sim Est_{post} + 1|$participants, where $\sim$ stands for "predicted from" and $1|$participants read as "random intercept across participants." In the model, Est_{post} refers to the posterior estimations calculated with Eq. 2. Finally, the experimental conditions are embedded in the calculation of posterior estimations (i.e., Est_{post}) with different values of CV_{social} across experimental conditions.

We also investigated the effect of social and first estimations on the change of mind. Accordingly, if participants change their minds in a Bayes optimal fashion by taking the

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mean and precision (CV) of the social estimates into account, there should be a positive linear relationship between social estimation mean and change of mind. Critically, this relationship should be stronger for high social estimate precision (i.e., lower social estimation CV). To test this hypothesis, we conducted another linear mixed effects model where we used the change of mind as the dependent variable. To this end, we subtracted the first estimations of the participants from their second estimations to operationalize the change of mind (negative values depict a change of mind toward lower values, and positive values depict a change of mind toward higher values). We also added the absolute difference between the first estimate of the participants and mean estimates of the mock participants to the model as a control variable (hereby referred to as "social difference"). Consequently, we conducted the following model depicted below:

Model 2: Change of mind $\sim$ social estimation CV * social estimation mean + social difference + 1|participants

We performed two analyses with this model. First, we discarded all trials where participants did not change their mind. As a result of this elimination, 76% of the whole dataset was removed. In the second analysis, we included all trials irrespective of whether or not participants changed their mind. Note that the number of trials with no change of mind did not change across experimental conditions (all ps $> .05$). In order to ensure that our results were not because of this exclusion, in the second analysis, we included all trials irrespective of whether or not there was a change of mind. The models included all lower terms (i.e., the main effects) for both analyses. For all statistical analyses, we used an alpha level of 0.05 for the significance testing.

4. Results

The first linear mixed effects model (Model 1) revealed a significant positive linear relationship between posterior estimations and the second estimations made by the participants (ß = 1.23, $SE = 0.01$, $p < .001$, 95% Confidence Interval (CI) = [1.21, 1.25]; conditional $R^2 = 0.64$). Fig. 1b depicts the relationship between the posterior estimations and second estimates.

The second linear mixed effects model (Model 2; conditional $R^2 = 0.23$) revealed a significant main effect of social estimation CV on change of mind, which refers to the difference between the target normalized second and first estimations (ß = −0.33, $SE = 0.14$, $p = .03$; 95% CI = [−0.61,−0.05]), revealing a decrease in change of mind as the social estimation precision (i.e., how precise/close together the social estimations are) decreases. This result is in line with the prediction that participants would rely more on social estimations as the estimation precision of the group increases.

A similar relationship was observed between the social estimation mean and the change of mind (ß = 0.51, $SE = 0.04$, $p < .001$; 95% CI = [0.43,0.60]), revealing that participants increased their second estimations according to the increased target normalized social estimation mean. This finding suggests that participants adjust their estimations according to the social estimation means.

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Finally, there was an interaction between the social estimation CV and the social estimation mean on the change of mind ($ß_{\text{social estimation CV * social estimation mean}} = -13.60$, $SE = 2.15$, $p < .001$; 95% CI = [−17.82, −9.39]); as CV of the social participants' estimations increase (i.e., as the social estimation precisions decreased), the relationship between social estimation mean and change of mind decreases. This result points to the idea that participants rely their estimations less on the social participants' mean estimates. Furthermore, there was a significant main effect of social difference on change of mind ($ß = -0.51$, $SE = 0.02$, $p < .001$; 95% CI = [−0.55, −0.47]), demonstrating a negative update in the second estimation as a result of increased deviance between the first estimations and social estimations (independent of the precision of the social information).

We also ran Model 2 by including the trials where no change of mind occurred (conditional $R^2 = 0.087$). As in the case of the model where these trials were discarded, the main effect of social estimation CV on change of mind was significant ($ß = -0.09$, $SE = 0.04$, $p = .021$, 95% CI = [−0.16, −0.01]). There was also a main effect of social mean estimates on change of mind ($ß = 0.13$, $SE = 0.01$, $p < .001$, 95% CI = [0.11, 0.15]). Finally, there was a significant interaction between the social estimation mean and CV on change of mind ($ß_{\text{social estimation CV * social estimation mean}} = -3.87$, $SE = 0.56$, $p < .001$, 95% CI = [−4.96, −2.78]). These results demonstrate that the overall behavioral pattern remained unchanged when the trials without a change of mind were included in the analysis.

We also investigated whether the absolute change of mind differed across high and low social mean conditions. Linear mixed-effects demonstrated no difference between low and high mean social conditions in terms of the amount of change of mind ($p = .68$; 95% CI = [−0.007, 0.011]), revealing that the amount of change of mind does not depend on the direction of social mean values with respect to the participants' own statistics. Finally, we compared the variance of the first and second estimations to further investigate the Bayes optimal response updating. Accordingly, if participants updated their initial responses in a Bayes optimal way, the second estimations should have lower variance than the first estimations. Paired sample t test revealed higher variance for the first estimation compared to the second ($t(38) = 6.53$, $p < .0001$; 95% CI = [0.003, 0.006]), which further validates the hypothesis of Bayes optimal response updating. Fig. 1c illustrates the comparison between first and second estimation variances.

5. Discussion

We found a positive relationship between change of mind and the mean of social estimates, pointing out a conformity toward the group mean estimation. Critically, though, this conformity was not blindly "obedient," how much participants conformed to the group mean was determined by the group estimation CV, which indexed the group certainty or social "consensus" and provided a reliability index for the participant. More specifically, participants conformed to the group mean estimations when estimations of the group members were in consensus (i.e., low CV) with respect to the participants' baseline estimations. This conformity pattern, however, decreased as the group consensus was relatively diminished in the high

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CV condition of the social blocks. Importantly, this behavioral pattern persisted when the trials without change of mind were also included in the model. Together, these results point to an overall response pattern that conforms to group estimations according to their reliability.

Along with the results regarding change of mind, we also investigated whether participants weigh these two sources of information (i.e., endogenous and social) according to their relative reliability (i.e., with respect to the other source of information) while making a second estimation. Our results revealed that the second-chance responses were a function of the weighted average of participants' and groups' estimations; while making a second estimation, participants integrate the two sources of information (i.e., endogenous and social) such that the more reliable source of information has a stronger effect on the second estimation. This result points to harsher (non)conformity as the reliability of (endogenous) social information increases, which is further validated with diminished variance in the second chance compared to the first estimations. Together, these results support the hypothesis that social conformity in magnitude estimates demonstrates a Bayes optimal way that credits social and endogenous information according to their reliability (Li et al., 2019).

Here, as the context lacks explicit feedback regarding the relative reliability of the social estimations with respect to the participants' own, the above-mentioned behavioral patterns indicate implicit metacognitive monitoring: Participants could keep track of their own uncertainty (i.e., CV of own estimates), make comparison with the group statistics, and weigh social information accordingly. Thus, the Bayes optimal way of response updating observed in the current study points to an implicit form of metacognition in a metric context. Seemingly, these results also align with the recent findings, which demonstrated that advice-seeking behavior was a function of subjective confidence (Pescetelli et al., 2021). In Pescetelli et al. (2021), participants were tested in a 2AFC task where they were asked to report whether the left or right stimulus was more numerous and their confidence. Results demonstrated that participants asked for advice even at a cost (costly advice block) when they were uncertain of the correct response. Thus, this result validates the correlation between subjective confidence and advice-seeking, which can be adapted to the implicit forms of metacognition as in the current study.

Although highly relevant to the current work, due to methodological limitations, the study design of Molleman et al. (2020) cannot disentangle whether the social conformity relied on the implicit comparison between the endogenous and social information statistics based on metacognitive processing. In their study, participants were explicitly given a hint regarding their own deviance from the group estimations as well as the group variance with an explicit visual cue (i.e., points on a sliding scale). This methodological choice renders the results hard to interpret within a metacognition framework; It remains unclear whether participants relied solely on the visual cues without necessitating any implicit calculation or monitoring processes during conforming the group.

Overall, with a different methodological and analytical approach, the current study replicates the findings obtained by Molleman et al. (2020). Thus, our results highlight the robustness of Bayes optimal conformity pattern observed in Molleman et al. (2020). Beyond merely replicating Molleman et al. (2020), the methodological approach in the current study resolves an important limitation by providing participants with the estimations of group members with numerical values. Our methodological approach required the participants to perform

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an implicit calculation of the social information statistics (i.e., the mean and variance of the social participants' estimations) and compare them with the endogenous estimate statistics. Accordingly, the standard deviation of the group estimation can hint at a consensus with the associated variance and, thus, the overall confidence/reliability level of the group where high consensus represents high reliability. Together, our results demonstrated that human response updating is Bayes optimal even without necessitating explicit visual cues that sign the deviation from the group (as in Molleman et al., 2020).

A recent study by Pezzulo, Roche, and Saint-Bauzel (2021) demonstrated that subjective confidence can be implicitly inferred from the force applied during motor actions such that pushing harder toward one of the two response options implies high confidence. This finding is in line with the idea that the confidence of other individuals can be implicitly inferred from other behavioral cues instead of explicit confidence reports, which is also consistent with the findings obtained in the current study. However, their study, too, falls short of explaining the contribution of metric characteristics of the errors to the social conformity patterns. Thus, our study is the first to show that Bayes optimal way of social conformity can be guided by the implicit calculation and inference of group reliability in the social conformity literature without relying on direct spatial cues as in Molleman et al. (2020). Finally, our study adds novelty to the current literature by demonstrating the metric characteristics of social conformity instead of having a "conform or not" nature. Our study can capture the "amount" of how much participants update their initial responses (thus conform) as a function of the social estimation statistics.

We did not include a manipulation check where we asked whether participants indeed thought that the mock participant estimates belonged to actual participants that completed the study before. Nevertheless, the behavioral results that point to social conformity according to the relative reliability verify the effectiveness of our experimental manipulation, which can also serve as an inherent form of manipulation check. Thus, we do not have a theoretical explanation for why participants would conform according to the mock stimuli they did not believe to belong to a real person. One advantage of the weighted average approach for Bayesian integration comes from its inherent simplicity for addressing the current research question. As an alternative approach, future studies can use Bayesian posterior distributions to test whether similar conformity patterns can be replicated with other empirical approaches.

Future studies have yet to investigate whether the neural correlates of this kind of implicit integration of metric information are parallel to categorical decisions. Future studies should also replicate the findings in other metric domains, such as time and space. Such an investigation would broaden the scope of metric characteristics of social conformity. Future studies can also investigate the dynamics of social conformity in explicit forms of metacognitive monitoring by asking participants to indicate their subjective confidence level regarding their estimation performance. Such an investigation could more explicitly demonstrate the relationship between subjective confidence and social conformity. Moreover, future studies can ask participants why they changed or kept their initial responses to more elaborately investigate the metacognitive dynamics of conformity processes in metric estimations. Finally, future studies should replicate this study by testing the participants in a real group setting simultaneously to induce a more realistic social dynamic.

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6. Conclusion

This study revealed that participants adjust their numerosity estimates in a Bayes optimal fashion by weighting the contribution of social numerical estimates based on their uncertainty relative to participants' endogenous uncertainty. The findings point to the informational complexity of implicit metacognitive processes in metric domains.

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Conflict of Interest Statement

The authors have no conflict of interest to disclose.

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