Social information benefits the wisdom of individuals in the crowd

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Lorenz and colleagues (LRSH; 1) claim that social influence undermines the wisdom of the crowd (WOC) effect (where averaging real-world estimates from different individuals often provides a better estimate of the true value than any of the individual estimates). LRSH asked asking participants to estimate quantities multiple times, and found that making previous estimates public—by presenting either an average or the individual estimates from previous rounds—led to a reduction in variance between individual estimates. Although LRSH argued that this undermines the WOC effect, their results testify to the usefulness of information sharing to individuals in the crowd.

One recognized advantage of statistical multilevel modeling is the "shrinkage" of the variance of individual estimates when they are informed by group-level knowledge; in particular, more extreme estimates will be reined in (2). LRSH's results appear to show a similar benefit of group-level knowledge shrinking the range of individual estimates; indeed, LRSH's procedure bears similarities to Monte Carlo Markov chain sampling for multilevel models, in which sampling of group-level and individual-level information is interleaved (3). The benefits obtaining from shrinkage can be shown by calculating the average reward obtained by participants under LRSH's different information conditions. Figure 1 shows a divergence in reward between conditions, with a clear benefit in the full and aggregate conditions after five rounds of estimation. Figure 1 also plots the increase in confidence in the full and aggregate conditions observed by LRSH. Although LRSH claimed that this reflected a detrimental effect of social information (since the increase in confidence was not linked to an increase in accuracy of the group average), comparison of the two panels suggests that the increase in confidence of participants' in their own performance in the information conditions is calibrated to an external metric of performance, reward. These positive benefits of information sharing agree with those from domains such as foraging (4).

LRSH's claim also rests on their observation that sharing information increased the probability that the true estimate fell outside the range of median estimates. It should be stressed that this ordinal “bracketing” metric does not reflect an absolute worsening of performance (see LRSH’s Figure 1); by implication, social influence does not impair consensus formation in scenarios such as the IPCC (an example given by LRSH). Instead, the shrinkage shown above to be beneficial to individuals’ estimates gives the aggregate WOC measure a tougher baseline to compete against. Indeed, the bracketing metric used by LRSH blindly rewards excessive variance (that is, inaccuracy) in individual’s estimates, since increasing this variance will tend to increase the distance between the median estimates. The open question is whether the individual estimates in LRSH's paradigm are subject to *over*-shrinkage (which LRSH interpret as over-confidence). This is relevant, for example, in determining standard errors on projected changes in global temperature, but can only be determined experimentally by specifying an appropriate amount of variance in estimates against which the observed variance can be measured, which in turn requires quantifying the uncertainty at the level of groups and individuals.

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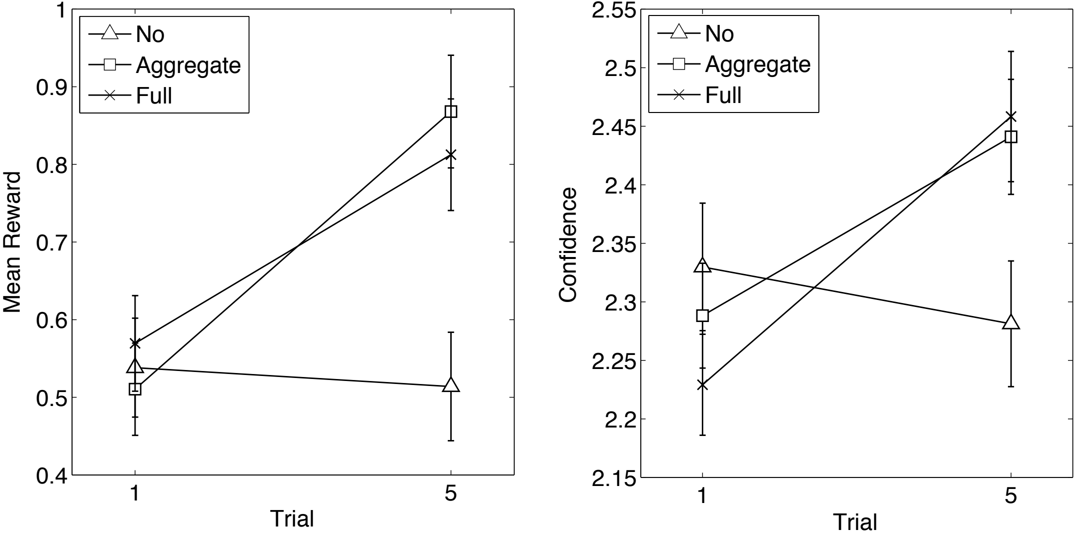
FIGURE CAPTIONS

Figure 1. Left panel: Mean reward per estimate in the three information conditions (separate lines) as a function of trial in the sequence of 5 estimations. Right panel: Mean confidence ratings. Error bars depict repeated-measures standard errors on the plotted means (5).


No
Aggregate
Full
Mean Reward
Trial
1
5
0.4
0.5
0.6
0.7
0.8
0.9
1
Confidence
2.15
2.2
2.25
2.3
2.35
2.4
2.45
2.5
2.55