Supplementary Material

This material contains additional details describing the model from Luhmann and Rajaram (2015), and a detailed analysis of the model's predictions across a range of parameter values.

Agent-Based Model: Methods and Results

In the model described by Luhmann and Rajaram (2015), agents encode N items (words), where N=40. Agents have two representations. The first is an activation vector $\mathbf{A}$ of length N. Each entry $\mathbf{A}_j$ gives the probability that the jth item will be retrieved. The second representation is an inter-item association matrix $\mathbf{S}$ of size $N \times N$. Each entry $\mathbf{S}_{ij}$ gives the jth item's (possibly asymmetric) association with the ith item. This matrix would normally contain agents' prior knowledge about word associations; however, Luhmann and Rajaram (2015) assigned values of $\mathbf{S}$ randomly between -2 and 2 to reflect agnosticism about the semantic relationships between words. (Neither the activation vector $\mathbf{A}$ nor association matrix $\mathbf{S}$ were used in our empirical studies because they were not applicable: we did not have access to participants' internal memory representations, nor did we test the theory that participants' updated these representations based on (randomly-selected or otherwise) semantic associations between words.)

The agents are exposed to items one by one, encoding them. The first step in encoding an item is to reduce the activation of the maximally active item in vector $\mathbf{A}$, where β is the learning rate:

$$\Delta \mathbf{A}_{\max} = -\beta \mathbf{A}_{\max} \ . \tag{1}$$

Next, the agent reduces the activations of items semantically associated with the maximally active item:

$$\Delta \mathbf{A}_j = -\beta \mathbf{S}_{j,\max} \mathbf{A}_j \ . \tag{2}$$

Finally, the agent increases the activation of the to-be-encoded item, with α acting as the learning rate:

$$\Delta \mathbf{A}_i = \alpha \Big[1 - \mathbf{A}_i \Big] \ . \tag{3}$$

The activation vector is then normalized to ensure that its entries can be interpreted as probabilities: $\sum_i \mathbf{A}_i = 1$.

During recall, an agent retrieves (and "orally states") an item. Agents take turns retrieving items, and on each turn, an agent retrieves an item with probability γ. Items are retrieved according to $\mathbf{A}$, such that items with higher activations are more likely to be retrieved.

The act of retrieving an item modifies the activation vector for both the retriever and the other members of the group. First, the agent decreases activation of items semantically associated with the retrieved item, in line with the theory of retrieval disruption:

$$\Delta \mathbf{A}_j = \beta \mathbf{S}_{ji} \mathbf{A}_j \ . \tag{4}$$

Next, if the ith item is not the maximally activated item, the agent reduces the activation of the maximally active item according to Equation 1, and the activations of items semantically associated with the maximally active item according to Equation 2. Item i is then encoded according to Equation 3. $\mathbf{A}$ is then normalized such that $\sum_i \mathbf{A}_i = 1$. Just as the retrieving agent encodes the item after retrieving it, "listening" agents also then encode the item according to the encoding process described previously. Luhmann and Rajaram (2015) used the following parameter settings: α=0.2, β=0.05, and γ=0.75.

Model predictions were generated by presenting agents with wordlists and then having agents recall words via the described procedure. When an agent generated a word, it was shared with every other agent in the network. Agents participated in 20 rounds of retrieval within each simulation. A total of 1000 simulations (comparing 1000 collaborative and 1000 nominal results) were run for each group size.

This model makes implicit assumptions through its paradigm choices, for example by using a turn-based paradigm with words "read aloud" to agents. In our empirical experiments, we tried to match these model choices as closely as possible, to best compare our behavioral results to model predictions. However, an exception is that in the modeling work, agents were allowed to submit any word that they had not previously retrieved, whereas in the behavioral work, participants were not allowed to recall words that they or any other group members had previously recalled.

Model Comparison: 40 words vs. 60 words

In Luhmann and Rajaram (2015), the authors use the following parameter settings to generate their model predictions: 40 words, α=0.2, β=0.05, γ=0.75, number of rounds=20, number of simulations=1000. Using these settings, they predict the following set of results:

> "As groups grew from 2 to 7 agents, collaborative inhibition increased (a finding that replicates and extends those of Basden et al., 2000, and Thorley & Dewhurst, 2007). In this range, the performance of both collaborative and nominal groups increased steadily. However, each additional group member conferred a much larger benefit to nominal groups than to collaborative groups. This effect of group size was probably driven by the relative balance between the facilitative effects offered by collaboration (i.e., more agents increased the probability that the group would retrieve a given item) and the detrimental effects of retrieval disruption (i.e., more collaborators meant more opportunities to be disrupted). Collaborative inhibition decreased as group size increased beyond 7. This effect was driven by the fact that nominal groups reached ceiling far earlier than the collaborative groups. Nonetheless, the continued deficiencies exhibited by even large collaborative groups suggest that the cognitive factors that hurt retrieval diversity in small groups could not easily be overcome by the addition of group members."

In our work, we use the code from Luhmann and Rajaram (2015) to generate model predictions with the number of presented words set at 60 rather than 40. As such, we do not expect to see collaborative inhibition peaking at a group size of 7, since this is an arbitrary number responsive to the parameter settings. However, we do expect to see the general trends Luhmann and Rajaram (2015) describe: collaborative recall increasing with group size, until nominal recall reaches ceiling performance as the disruption of idiosyncratic recall strategies is compensated for by sheer group size. The model will predict that from this point collaborative inhibition begins to decrease, since collaborative inhibition is the difference between nominal and collaborative recall. With our parameter settings, nominal ceiling performance occurs around group size 16. Note that we use identical parameter settings to Luhmann and Rajaram (2015) except for using 60 words, chosen because pilot studies indicated participants were nearing ceiling performance at small group sizes. Here we provide a comparison of the figure originally used in Luhmann and Rajaram (2015), using 40 words, compared to the model predictions generated using 60 recalled words (Figure S1).

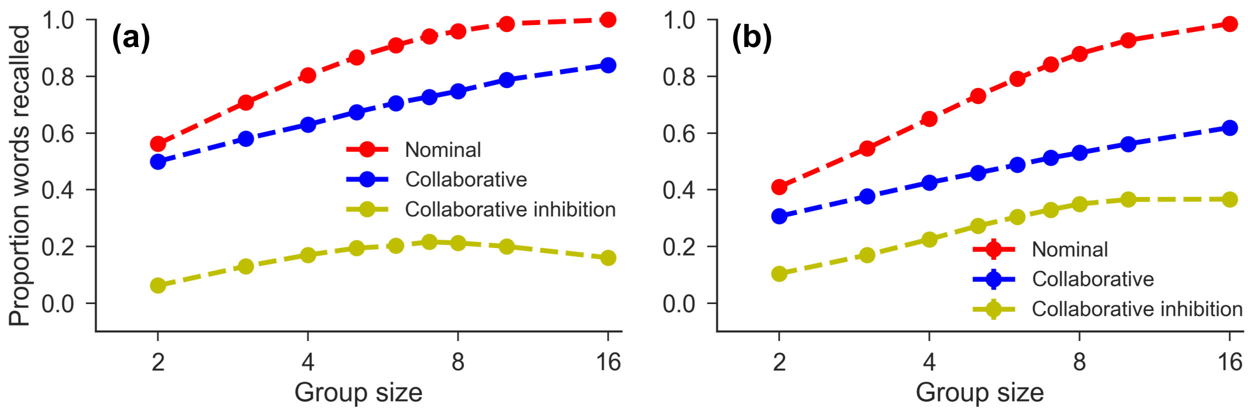

Figure S1. Comparison of model predictions for 40 vs. 60 recalled words. (a) Model predictions reproduced from Luhmann and Rajaram (2015), using parameter settings: 40 words, α=.2, β=.05, γ=.75, number of rounds=20, number of simulations=1000. Nominal recall (red/grey), collaborative recall (blue/black), and the subtraction of the two, collaborative inhibition (yellow/light-grey) are shown. (b) Model predictions produced using code from Luhmann and Rajaram (2015), using 60 words but otherwise identical parameters settings.

Varying Parameter Values

To examine the range of parameter values that might a larger collaborative inhibition effect for smaller groups than larger groups, we conducted a grid search centered on the parameters in Luhmann and Rajaram (2015) (α=0.20, β=0.05, γ=0.75, number of rounds=20), with 60 words. We ran 1000 simulations for each of the following parameter combinations: α=[0.1,0.2,0.3]; β=[0,0.05,0.10]; γ=[0.55,0.65,0.75,0.85,0.95]; number of rounds=[10,20,30]. For each parameter combination, we tested whether the model would predict a larger collaborative inhibition effect for the average recall of group sizes 2, 3, and 4 compared to the average recall of group sizes 8 and 16, to match what we observed empirically.[1] We also placed the constraint of needing at least some collaborative inhibition for group sizes 2, 3, and 4: specifically, the average collaborative inhibition effect had to be greater than 0.01 (109/135 of the parameter combinations met this criteria). We placed this constraint because we considered it necessary for the model to predict collaborative inhibition at small group sizes to match our results.

In 9/109 of the parameter combinations, the model predicted a larger collaborative inhibition effect for group sizes 2, 3, and 4 than for group sizes 8 and 16, as was true in our empirical data. However, all of those nine parameter combinations included setting the number of rounds to 30 (Figure S2). As rounds increase, agents have more chances to recall words and reach ceiling performance more rapidly. Since the collaborative inhibition effect is the difference between nominal and collaborative group recall, if ceiling performance for both the nominal and collaborative groups is reached, collaborative inhibition decreases. These simulation results (Figure S2) show that if ceiling performance had not been reached as rapidly, collaborative inhibition would have increased rather than decreased with group size. Thus, even though for these parameter settings the model predicts decreased collaborative inhibition at larger group sizes, this effect can be explained by ceiling performance effects. This is not the pattern of results we see in our empirical data, in which larger group sizes show decreased collaborative inhibition without ceiling-level performance.

[1] In the empirical results, the collaborative inhibition effect as measured as the difference of proportion of words recalled was the following: the average of group sizes 2, 3, and 4 was 0.05 (Experiment 1) and 0.10 (Experiment 2), and the average of group sizes 8 and 16 was 0.03 (Experiment 1) and 0.03 (Experiment 2).

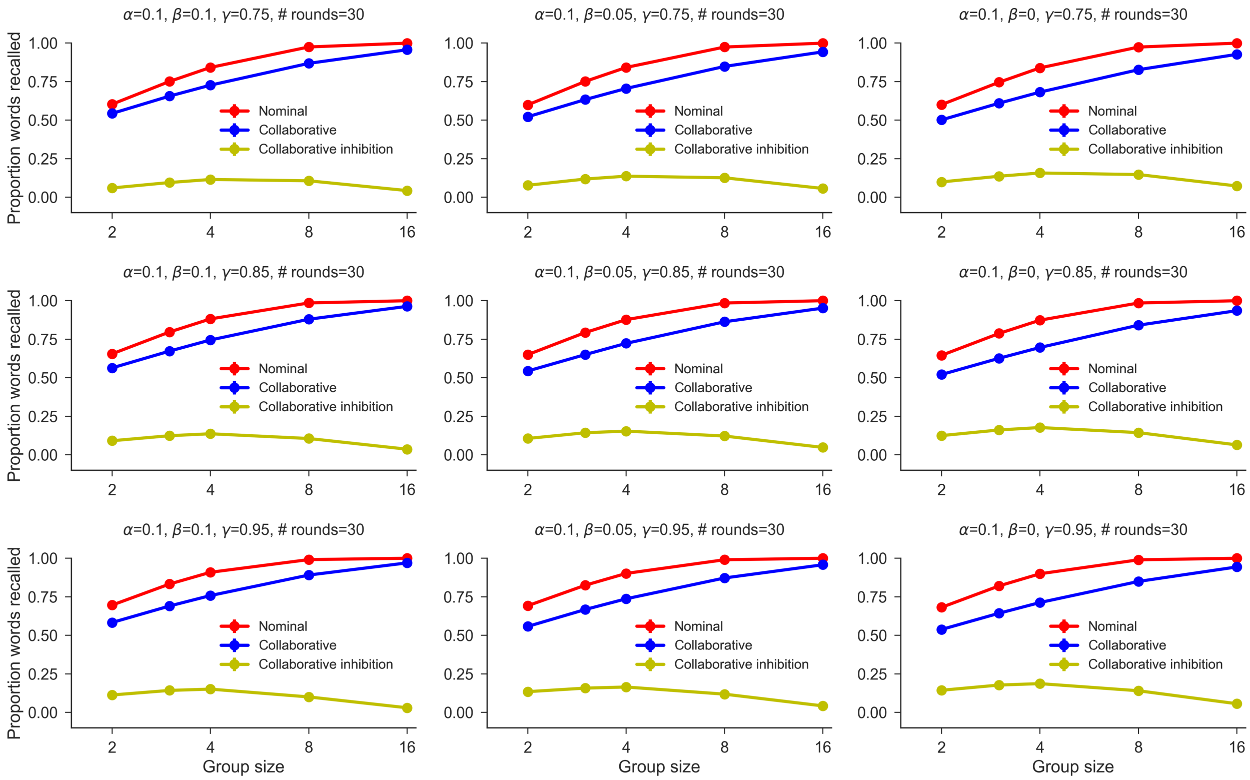

Figure S2. Parameter settings in which the model predicted a larger collaborative inhibition effect for the average recall of group sizes 2, 3, and 4 compared to the average recall of group sizes 8 and 16, constrained to simulations where there was an average collaborative inhibition effect for group sizes 2, 3, and 4 greater than 0.01. We ran 1000 simulations for each of the following parameter combinations: α=0.1, 0.2, 0.3; β=0, 0.05, 0.10; γ=0.55, 0.65, 0.75, 0.85, 0.95, number of rounds=10, 20, 30.

The model's predictions are even more inconsistent with our results when considering parameter combinations in which the number of rounds was 10 or 20: the model predicts that collaborative inhibition will increase at larger group sizes, rather than decrease. We thus observed that the model predictions did not qualitatively match empirical results across a variety of parameter settings, and when the model did predict larger collaborative inhibition at small group sizes, this was due to ceiling performance effects.

References

Luhmann, C., & Rajaram, S. (2015). Memory transmission in small groups and large networks: An agent-based model. *Psychological Science*, *26*, 1909–1917. https://doi.org/10.1177/0956797615605798