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An experimental study of the formation of collective memories in social networks☆

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ABSTRACT

The psychological research on the formation of collective memories has explored how individuals come to hold similar memories following conversational interactions in social networks. These collective memories are dependent on both individual-level cognitive mechanisms as well as on the social influence exerted during people's conversations. Building on this work, we investigate the impact of the network structure of conversational interactions on the formation of collective memories in 16-member networks. We manipulate two parameters of conversational networks that were previously found to impact information diffusion in networks: network reachability and network clustering. We find that clustering significantly impacts the emerging collective memory, but reachability does not. Additionally, a participant's influence on the content of the network's collective memory depends on both their topological position in the network and on how early their conversations occur in the conversational network.

1. Introduction

Communities of individuals oftentimes form similar memories of the past (Wang, 2008). For instance, consequential public events such as the September 11 attacks are remembered by many Americans and in similar ways (Hirst, Yamashiro, & Coman, 2018). Given the centrality of these collective memories for group identity (Zerubavel, 2003) and collective behavior (Bahrami et al., 2012), psychologists have started to empirically explore their formation (Hirst et al., 2018; Roediger & Abel, 2015). At an individual level, the malleability of human memory was found to facilitate the synchronization of memories following conversational interactions (Coman & Hirst, 2012; Rajaram & Pereira-Pasarin, 2010). At a community level, the network structure that characterizes a community's interactions was shown to affect the degree to which the community converged on a similar memory of the past (Coman, Momennejad, Geana, & Drach, 2016; Luhmann & Rajaram, 2015). But despite the burgeoning literature on the formation of collective memories, there is limited research that explores how the configuration of the conversational network structure in the community impacts the formation of collective memories (Vlasceanu, Enz, & Coman, 2018). Such an investigation has the potential to illuminate how the position of an individual in the social network (topological centrality) as well as the timing of her conversations in the network (temporal primacy) impacts the content of a community's collective memory.

One important factor that facilitates the community-wide memory synchronization is that people communicate with one another about their memories. The social influence processes triggered during communicative interactions lead to the alignment of the conversational partners' memories (Coman, Manier, & Hirst, 2009; Edelson, Sharot, Dolan, & Dudai, 2011). Following exposure to an event, information that is discussed tends to be strengthened (Barber, Rajaram, & Fox, 2012), while information that is related to what is discussed, but unmentioned, tends to be forgotten by both conversational partners (Cuc, Koppel, & Hirst, 2007). To explore these synchronization dynamics at a dyadic level, researchers ask pairs of participants to study stories characterized by a category-exemplar format (e.g., the "Trip to Coney Island" category is comprised of "eating ice-cream" and "walking on the beach;" while "School-day" is comprised of "eating lunch" and "taking a test"). Following this exposure, participants are instructed to jointly

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recall the studied story. Typically, during these conversations, participants selectively recall the previously studied information (Marsh, 2007). The mentioned exemplars are labeled as Rp+, while unmentioned exemplars from the same category constitute Rp-. Unmentioned exemplars that belong to a different category than the mentioned one constitute the Nrp items. Finally, an individual recall test follows for both participants. A *practice effect* is observed when, in the final recall, Rp + items are remembered better than Nrp items. A *retrieval-induced forgetting effect* is found when Rp- items are remembered worse than Nrp items. Importantly, both the speaker and the listener experience practice effects and retrieval-induced forgetting effects. The effects that pertain to the listener - labeled as socially-shared practice and socially-shared retrieval-induced forgetting effects – are due to the concurrent retrieval on the part of the listener (Cuc et al., 2007) and have been shown to be facilitated by speaker-listener similarity (Barber & Mather, 2012), social identity (Coman & Hirst, 2015), and emotional relevance (Coman & Berry, 2015). Importantly, when both interaction partners experience similar practice and retrieval-induced forgetting effects, their memories become similar to one another's (Coman & Hirst, 2012).

But dyadic-level synchronization facilitates the formation of collective memories across the community only when the social influence one individual exerts over another propagates through the community. We aim to investigate the two network parameters that were previously found to impact information dissemination through the network: clustering and reachability (Borgatti, 2005). Coman et al. (2016) showed that clustered communities (i.e., in which individuals frequently communicate with other individuals from their sub-group and infrequently with individuals from neighboring sub-groups) form fragmented collective memories (see also Choi, Kensinger, & Rajaram, 2017). This research suffers, however, from two limitations. First, the experimental procedure created only a small variation in how central participants were in the network, which limited the investigation into how an individual's network position impacts the community's collective memory. Second, the clustering coefficient was manipulated to only be low or moderate. This precluded the investigation of network structures more representative of real-world communities, characterized by a high clustering coefficient and high reachability (Watts & Strogatz, 1998).

The mnemonic convergence of a community does not solely depend on how clustered a community is, but also on the degree to which information mentioned by individuals can reach other individuals in the network (Durrett, 2010). Communities in which information that individuals discuss can only reach a small number of neighbors (i.e., low reachability) are less likely to converge on collective memories because the influence one individual has over another does not propagate efficiently. In previous research, we found that both the practice and the induced forgetting effects only propagate three degrees away from the originating source (Drost-Lopez & Coman, 2018). Based on those findings we predict that networks with high reachability (i.e., information provided by an individual can reach many other individuals in the network) will form more convergent memories than networks with low reachability.

In most networks, clustering and reachability are highly inter-correlated, which makes it difficult to disentangle their separate effects on collective phenomena. Highly clustered networks tend to have low reachability, since only a limited number of nodes are connected across clusters. In the present study, we attempted to explore their independent impact on the formation of collective memories by using an experimental approach. We created four types of conversational networks by manipulating the networks' clustering coefficient and average reachability. We predict that clustered networks in which individuals who bridge between clusters communicate first will form more convergent memories than non-clustered networks. This is due to the fact that information discussed by individuals who connect between clusters (i.e., bridge ties) is subsequently rehearsed within clusters, which leads to community-wide synchronization of memories. Similarly, we predict that networks whose individuals have high reachability will experience more mnemonic convergence compared to networks that are low in reachability.

Critically, manipulating network clustering and reachability offers the possibility to investigate whether some individuals are more influential than others in shaping the community's collective memory. We test the hypothesis that individuals that bridge between different sub-communities in a network (topological centrality) and those who have their conversations early on during the community's interactions (temporal primacy) exert more influence at a collective level than topologically and temporally peripheral individuals.

2. Methods

2.1. Participants

A total of 192 Princeton University students were grouped into twelve 16-member networks. The stopping rule for participant recruitment was established based on the effect size obtained in a previous study that used aggregate measures of collective memory in networks (Coman et al., 2016). A sample size of 12 networks was deemed adequate, given that the aggregation procedure, which involves averaging over all pairwise scores within each network (i.e., 120 scores per network) drastically reduces the standard deviation in each condition and increases the effect size. We set one a priori exclusion criterion involving recall proportion: an individual recall score of 2.5 standard deviations below the average recall of the sample. This pre-established criterion was used because inadequate engagement with the materials had the potential to influence other participants in the conversational network. Seven percent of participants (13 out of 192) met this exclusion criterion. Three networks in which 3 participants or more met the exclusion criterion were discarded from analyses, as the low engagement from these participants affected the nature of the conversational recalls for a majority of participants in these networks. Low-engagement participants provided very little information during the conversational recall and did not actively engage with the information mentioned by their conversational partners. Note that this non-compliance exclusion criterion is unlikely to be systematically affected by the manipulation, since participants across all networks experienced the exact same experimental situations (e.g., stimulus materials, number of conversations, number of neighbors). The manipulation solely targeted the conversational network structure and so we are confident that the participants' experience throughout the experiment was similar across conditions.

In total, 144 participants (62% female, M = 21.62, SD = 3.81), grouped in nine 16-member networks were included in final analyses. We used the G*Power calculator to estimate the statistical power for the current study based on the effect sizes obtained in a similar study involving aggregation in networks (Coman et al., 2016). Thus, based on the number of networks retained in the analyses, we had an 0.87 power to detect an effect size η^2 of 0.60 for the interaction between variables in a mixed ANOVA design, a 0.78 power to detect an effect size of Cohen's d of 1.5, and a 0.99 power to detect a correlation of 0.4. The study was approved by Princeton University's IRB.

2.2. Stimulus materials

We created a Powerpoint presentation describing the events that happened to Brett, a fictional character. The presentation consisted of separate events that occurred during each of 6 consecutive days. For instance, on Sunday, Brett had an elevator incident, while on Monday, he had a bike accident. Each day (i.e., category) contained between 4 and 6 episodes (i.e., exemplars), and each episode was comprised of a brief sentence and a representative photo (Fig. 1C for an example and *Appendix 1* for a transcript of the story).

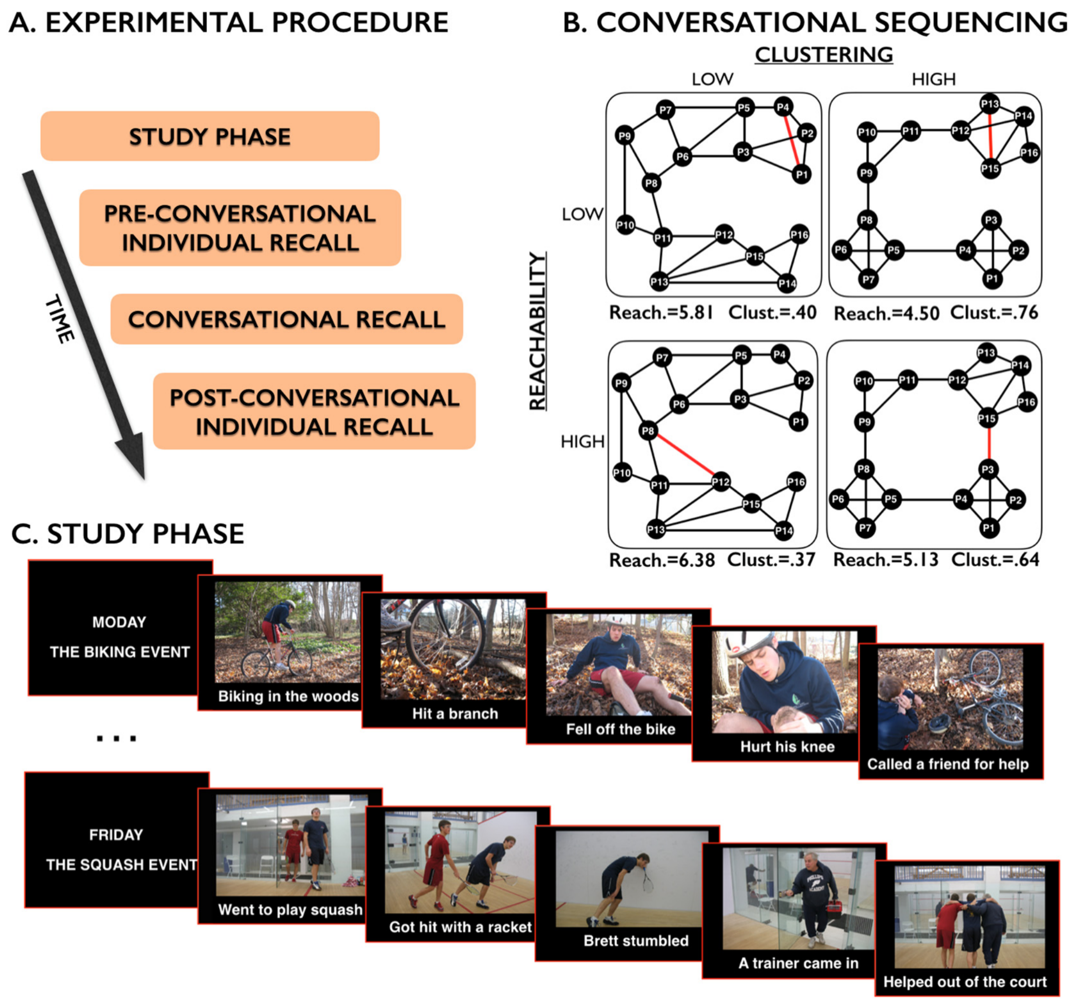


Fig. 1. Experimental paradigm. **A.** *Experimental procedure.* Sixteen participants (in each network) first studied a story characterized by an episode-event structure. They then individually recalled the story, after which each participant engaged in a sequence of 2–4 conversations to jointly recall the story. They then individually recalled the story once more. **B.** *Conversational sequences for the four network structures.* Nodes represent participants; edges in black represent conversational rounds; edges in red represent the differences among the different networks (see *Appendix 2* for the temporal order of conversations). **C.** *Event-episodes story.* Participants saw six events, each corresponding to incidents experienced by a character named Brett over the course of 6 days; each event consisted of five to six separate episodes (image-description associations). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2.3. Design and procedure

Each session was conducted with 16 participants who went through the experimental procedure together. This network size was selected for two reasons. First, in order to optimally vary both reachability and network clustering, one would need a network size of at least 12 individuals (i.e., three 4-member clusters). And second, the 16-member size allows for proper variation in both the number of conversations each participant had in the network (i.e., between 2 and 4) as well as in how early these conversations occurred.

Participants arrived in the lab at the same time and were physically present in the same room. They undertook the study in SoPHIE (Software Platform for Human Interaction Experiments), a platform specifically designed to allow for stimulus presentation and computer-mediated chat conversations. In the *study phase*, participants studied the story in a self-paced manner. They were told that their memory would be tested in a later phase. Then, in a *pre-conversational recall phase*, participants individually recalled as much as they could about the initially presented information. They then engaged in a sequence of dyadic conversations for which they were instructed to jointly recall the studied materials (*conversational recall*). Each conversation took place in a computer-chat environment and lasted for 150 s. The participants were informed that their conversational partners were physically present in the room, but did not know the identity of these partners, since all participants used avatars to identify themselves. Finally, another individual recall test followed (*post-conversational recall*) (Fig. 1A). Each participant in a 16-member community engaged in a sequence of two to four conversations, each involving turn-taking. The pre-conversational and post-conversational recalls were not time constrained, and across participants, they ranged between 4 and 8 min. Five-minute distracter tasks, in which participants completed unrelated questionnaires (e.g., Need for Cognition), were inserted between any two phases.

We created 4 different types of networks by manipulating the sequence of conversational interactions that took place in the network. These four network types were constructed by varying the clustering coefficient and the average reachability of the nodes in the network, essentially creating a 2 × 2 design: (a) High-Clustering/Low-Reachability network, (b) High-Clustering/High Reachability network, (c) Low-Clustering/Low Reachability network, and (d) Low-Clustering/High Reachability network (see Fig. 1B for parameter values and Fig. S1 *in Appendix 2* for the temporal order of the conversational sequences). We first employed a social network analysis software (i.e. UCINET) to create the structure of the networks according to the two dimensions (i.e., clustering and reachability). We tried several iterations to maximize the difference between low and high parameters on each of the two dimensions. We then assigned the temporal order of conversations in these structures, with the only constraint being that participants who bridged between the clusters (in the high clustering conditions) had the first conversation in the network. We then matched the conversational sequence in low clustering conditions to the high clustering conditions using two strategies. (1) We assigned an equal number of Round 1 conversations, Round 2 conversations, Round 3 conversations, and Round 4 conversations between the two condition types. And (2), we positioned these conversations in equivalent locations in the network between the two condition types. Importantly, we kept the number of participants and the total number of conversations constant across all conditions.

2.4. Coding

In these studies, we report all measures, manipulations and exclusions. Recall protocols were coded by a research assistant who was blind to the study's hypotheses. It involved a binary coding scheme in which an item was labeled as either remembered or not remembered. Ten percent of the data were double-coded for reliability ($\kappa = 0.86$). Disagreements were resolved through discussion.

For each network, mnemonic convergence scores were computed separately for the pre-conversational and post-conversational individual recalls. First, a *mnemonic similarity score* for each pair of participants in the network was calculated by adding the number of items remembered in common and the number of items forgotten in common by both participants, and then dividing this sum by the total number of items studied (Table 1). The *network mnemonic convergence score* was calculated by averaging all the pairwise mnemonic similarity scores in the network separately for pre- and post-conversational recalls.

2.5. Data availability

All data associated with this study is available on an open data platform at: https://osf.io/epncq/

3. Results

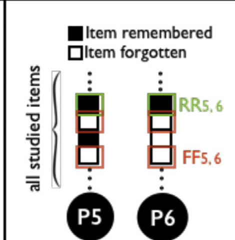
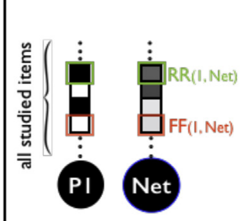
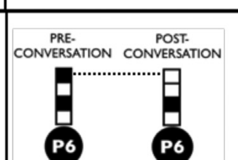
3.1. Pre-conversational, Conversational, and Post-conversational recall scores

First, we report the recall proportions for the individual and conversational recalls: M_{Recall} *Pre-conv.* = 0.66, *SD* = 0.18 and M_{Recall} *Post-Conv.* = 0.69, *SD* = 0.18. For the conversational recall, we consider the contributions of both participants in the dyad as the unit of analysis; the average recall proportion of all the conversational rounds across all networks is M_{Recall} *Conv.* = 0.47, *SD* = 0.08. We note that the rate of distortions is very low across individual and conversational recalls (< 5% of recalled items), given that we pretested the items to be concise and distinct from one another.

3.2. The influence of network structure on mnemonic convergence

We conducted a Mixed ANOVA with *Time* (Pre vs. Post) as a within-network variable, and *Clustering* (Low vs. High) and *Reachability* (Low vs. High) as between-network variables. The mnemonic convergence score, computed at a network level, constituted the dependent variable. We found a main effect for *Time*, $F(1,5) = 84.035$, $p < .001$, $\eta^2 = 0.94$

Table 1
Definitions, figures, and formulas for the dependent variables.

MEASURE/DEFINITION	FIGURE	FORMULA
MNEMONIC SIMILARITY Similarity between the memories of any two participants, computed both pre and post-conversation.		$MS_{i,j} = \frac{RR_{i,j} + FF_{i,j}}{N_{total}}$ ***RR*** - number of items participants i and j remembered (black squares) in common ***FF*** - number of items participants i and j forgot (white squares) in common ***N*** - total number of items studied
MNEMONIC CONVERGENCE Average of mnemonic similarity scores across a network, computed both pre and post-conversation.		$MC_{i:j} = \frac{\sum_j^i MS_{i:j}}{N_{i:j}}$ $MS_{i:j}$ - mnemonic similarity for all i-j pairs in a network $N_{i:j}$ - number of i-j pairs
INDIVIDUAL-NETWORK SIMILARITY Similarity between a participant's pre-conversational recall and the community's post-conversational average recall.		$\lvert Rec\ K_i - Rec\ K_N \rvert \leq c$, then K is RR/FF if K=1, then K is RR; if K=0, then K=FF **Recall** K_i - Recall status of item K by participant i **Recall** K_N - Average recall of item K by network N **c** - criterion for commonly remembered/forgotten items
MNEMONIC DIFFERENCE The difference between a participant's pre- and post-conversational recall, separate for each item		$MD_i = Rec\ A_i^{Post} - Rec\ A_i^{Pre}$ *Rec Ki* - Recall status of item K, for participant i, pre and post-conversational recall

and a significant interaction between *Time* and *Clustering*, $F(1,5) = 8.78$, $p = .031$, $\eta^2 = 0.637$ but not between *Time* and *Reachability*, $F(1,5) = 0.36$, $p = .57$, $\eta^2 = 0.007$. As predicted, highly clustered networks exhibited a larger increase in mnemonic convergence from pre-conversation to post-conversation ($M_{HighCl} = 0.089$, $SD = 0.029$), than less clustered networks ($M_{LowCl} = 0.040$, $SD = 0.022$),$t(7) = 3.63$, $p = .008$, d = 1.90, CI[0.015; 0.071]. In contrast to our hypothesis, networks high in reachability were no different from networks low in reachability in their degree of mnemonic convergence, $t(7) = 0.13$, $p = .90$, d = 0.20, CI[−0.034; 0.059]. We also conducted bootstrapping analyses to verify the stability of these findings with simulated data (see *Appendix 3*).

High clustering networks in which the first conversations occur between participants who connect clusters followed by within-cluster conversations facilitated the formation of convergent collective memories. We speculate that clustering might facilitate the convergence of memories in the network by efficiently synchronizing the participants' memories from one conversational round to another. If this is the case, we should find a monotonic increase in the similarity between participants' memories from one round to the next in the high-clustering networks and a smaller (or no) increase in low-clustering networks.

To test this conjecture, we computed the similarity between each conversational recall and the network's post-conversational collective memory. We first calculated the average post-conversational recall for each of the 34 items, separate for each network. For instance, if 12 of the 16 (75%) members of the network mentioned *Item 1* in the post-conversational individual recall, *Item 1* would have an average recall score of 0.75. Items that had scores above our criterion threshold of 0.75 were considered to be part of the group's collective memory; items that had recall scores below 0.25 were considered to be collectively forgotten. We note that using thresholds between 0.00 and 0.40 for collectively forgotten items and between 0.60 and 1.00 for collectively remembered items produced very similar results with the ones reported herein.

We next computed each conversation's mnemonic similarity to the network's post-conversational recall by adding the number of items that were present in the conversational recall and had post-conversational network scores larger than 0.75 and the number of items that were absent from the conversational recall that had post-conversational network scores smaller than 0.25 and dividing by the total number of items studied (i.e., 34 items). We then investigated how much each conversation's similarity to the network's collective memory changed across conversational rounds. We conducted a Mixed ANOVA with *Time* (Round 1 through Round 4) as a within-network factor and *Clustering* (High vs. Low) and *Reachability* (High vs. Low) as between-network factors. There was a significant main effect for *Time*, $F(3,18) = 5.39$, $p = .008$, $\eta^2 = 0.47$, with conversational recalls becoming more aligned with the post-conversational collective memory with each conversational round (Fig.2C). As predicted, there was a main effect for *Clustering*, $F(1,6) = 8.19$, $p = .029$, $\eta^2 = 0.57$, with clustered networks exhibiting more alignment with the community's collective memory with each conversation than non-clustered networks. There was no effect of *Reachability* or for the interactions.

Additional support for a convergence mechanism that involves efficient propagation of information in the clustered networks could come from exploring the role of bridge ties in synchronizing the memories of neighboring clusters. Momennejad, Duker, & Coman (2019), for instance, showed that if conversations first occur between individuals that bridge between clusters and then between individuals that belong to clusters than the mnemonic convergence across the community is significantly higher than when the first conversations first occur within-clusters and only afterwards between individuals that bridge between clusters. This is because the synchronization of memories between individuals that bridge between clusters seeps into subsequent conversations that take place within-cluster. We tested this conjecture by comparing the cross-cluster mnemonic similarity scores between the cluster comprising participants P1-P4 and the cluster comprising participants P12-P16. This comparison was only performed for high clustering networks, since the low clustering networks do not have boundaries that delimit specific clusters. The mnemonic similarity between P3 and P15 was not included in the analysis to ensure that the difference bewteen conditions is not due to that one conversation that was present in the Complete Bridge condition and absent from Fragmented Bridge condition. As expected, an independent *t*-test revealed that the Complete Bridge networks exhibited higher cross-cluster mnemonic similarity compared to the Fragmented Bridge networks ($M_{CompleteBridge} = 0.18$, $M_{FragmentedBridge} = 0.10$,$t(29) = 2.099$, $p = .04$).

3.3. Topological centrality and temporal primacy impacts the formation of collective memory

Given variation in the positioning of individuals in the networks, we set out to test whether individuals' centrality in the network impacts the community's collective memory. We differentiated between topological centrality (i.e., a participant's location in the network) and temporal primacy (i.e., early timing of the participant's conversations).

We first measured the betweenness centrality of all individuals in the network. Defined as the degree to which a node bridges between other nodes in the network, this measure was computed for all 16 individuals in the network (Freeman, 1978). For temporal primacy, we first computed a temporal order score for each participant using the temporal sequencing of their conversations. To do so, we averaged the round numbers in which the participant was involved. For instance, a participant who only conversed in Rounds 1 and 2 had a temporal order score of 1.5, whereas a participant who only conversed in Rounds 3 and 4 had a temporal order score of 3.5. We then weighed these temporal order scores by convolving an exponential function onto the linear weighing. This exponential weighing involved overweighting early rounds and underweighting later rounds, a procedure aimed at quantifying temporal primacy.

To measure each individual's influence on the network's collective memory, we computed an individual-network similarity score (*Table 1*). We again utilized the average post-conversational recall for each network, for all 34 studied items. Then, we computed a participant's mnemonic similarity to the network's recall by adding the number of items present in the individual's pre-conversational recall that were collectively recalled by the community post-conversation (recall scores > 0.75) and the number of items absent from the individual's pre-conversational recall that were collectively forgotten by the community post-conversation (recall scores < 0.25). We found a significant correlation between a participant's betweenness centrality and the individual-network similarity score, $r = 0.43$, $p = .02$ (Fig. 3A). This indicates that individuals who are topologically central are more influential in shaping the collective memory of the community than peripheral individuals. Similarly, a participant's temporal primacy score was correlated with the individual-network mnemonic similarity score, $r = 0.64$, $p = .03$ (Fig. 3B). A regression model using both topological and temporal primacy as predictors revealed that they both have significant, and separate, effects on the community's collective memory, $F(3,136) = 3.92$, $p = .01$, $\eta^2 = 0.078$ (β*topological* = 0.095, $p = .039$; β*temporal* = 0.22, $p = .006$).

Mnemonic sensitivity predicts alignment between individual and collective memory.

Jointly remembering previously studied information was found to result in both better recall for the mentioned information (i.e., rehearsal effect) as well as forgetting of the unmentioned, but related to the mentioned information (socially-shared retrieval-induced forgetting) (Coman et al., 2009). We reasoned that individuals who are most sensitive to social influence – captured by high levels of rehearsal and retrieval-induced forgetting effects following conversational interactions - should be the ones whose memories become more similar to the emerging collective memory.

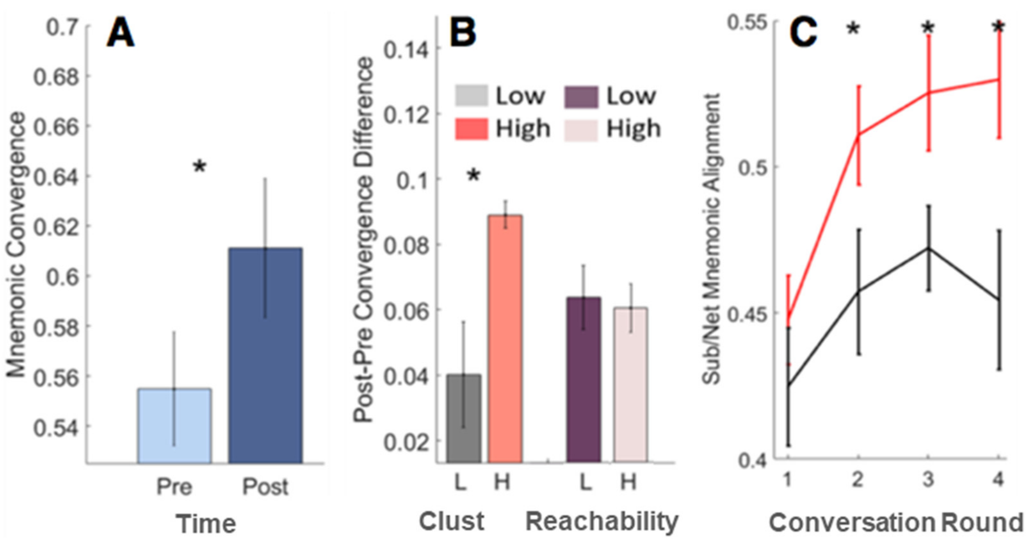


Fig. 2. Mnemonic convergence. **A.** Convergence scores before and after the conversational rounds across all network types. **B.** Post-Pre convergence difference for low (L)/high (H) average path length and clustering. **C.** Similarity between conversational recall (at each conversational round) and post-conversational collective memory, separate for high clustering (red) and low clustering (black) networks. Error bars represent SEM. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

To explore this conjecture, we first computed a mnemonic sensitivity measure for each participant with the aim of using this score to predict how aligned a participant's memories are to the emerging collective memory of the community. To construct a mnemonic sensitivity score, we followed Coman et al. (2016) and computed reinforcement/suppression (R/S) scores for each of the 34 studied items. If an item was mentioned during the participant's conversation, it received a (+1) score on the R/S scale; if an item was not mentioned during a conversation, but other items from that category were mentioned, it received a (−1) score on the R/S scale. Items unmentioned and unrelated to the mentioned items received scores of 0. Note that here categories refer to the different days of Brett's week. The cumulative R/S score for each item was calculated by summing the R/S scores across the conversations that each participant had in the network. The maximum number of conversations a participant could have was 4, which resulted in 9 R/S item types that ranged from −4 to 4. We next computed a *mnemonic difference score* by subtracting an item's pre-conversational recall score from its post-conversational recall score (*Table 1*). Finally, we averaged these mnemonic difference scores for each participant, separately for each R/S item-type (Fig.4A).

For a measure of mnemonic sensitivity, we computed the slope of the R/S score curve for each participant. The steeper the slope, the more mnemonic sensitivity; that is, the more the participant's memories were influenced by their conversational partners. A binomial test indicated that the majority of participants (119/144, $p < .001$) had slopes (betas) significantly higher than zero. An individual's mnemonic sensitivity was found to be marginally significantly correlated with the degree of mnemonic alignment between their post-conversation memory and the post-conversational collective memory of the network

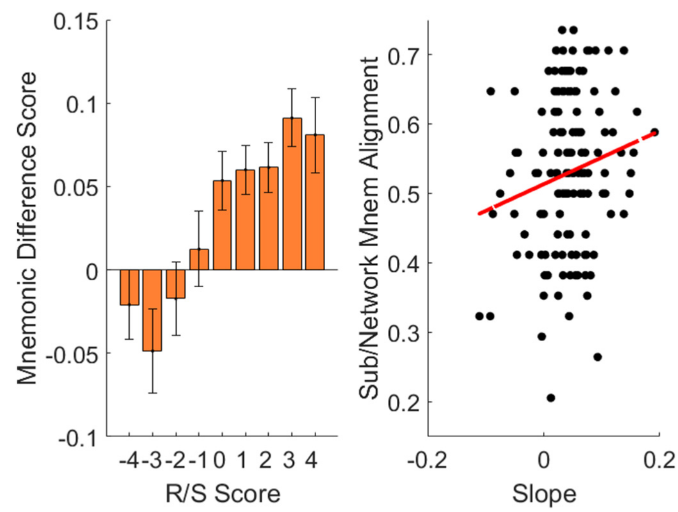


Fig. 4. A. Mnemonic difference scores by R/S type. Items with lower R/S scores show a suppression effect (negative mnemonic difference scores), whereas items with higher R/S scores show a reinforcement effect (positive mnemonic difference). **B.** The magnitude of the slope of the mnemonic difference curves for each participant correlates with the individual-network similarity score.

($r = 0.226$, $p = .063$, Fig. 4B). Based on these analyses, as well as previous studies that used a similar paradigm (Coman et al., 2016), we conclude that the collective memories of a community are shaped by the socio-cognitive processes triggered during the interactions among its members.

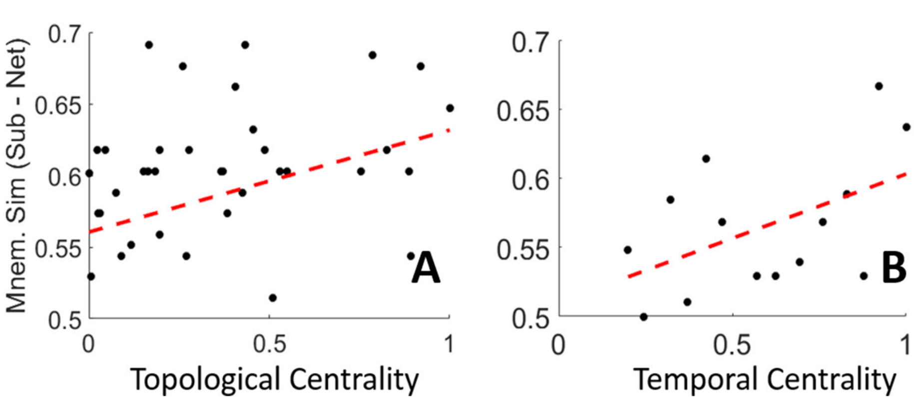


Fig. 3. Scatterplots of the correlations between topological centrality (Panel A) and temporal primacy (Panel B) and individual-network similarity score. Dotted red line represents best-fitting linear regression model. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4. Discussion

The present study advances the psychological literature on the formation of collective memories in at least three ways. First, we provide evidence that the mnemonic convergence a community reaches depends on both cognitive phenomena triggered in conversational interactions as well as on social influence processes. Second, we found that at a structural level, network clustering plays an important role in the formation of collective memories, while average reachability does not seem to make a difference. And third, at a local level, we show for the first time that one's position in the social network can affect the content of the community's collective memory, with more topologically and temporally central individuals being more influential in shaping the community's collective memories.

Importantly, the reported results were obtained using a paradigm that only created the minimal conditions for social influence to occur. We provided participants with limited information about their conversational partners and conversations involved computer-mediated interactions. Increasing the ecological validity of the paradigm would have predictable effects on the formation of collective memories. We speculate that presenting participants with more socially-relevant information about their partners (e.g., expertise, trustworthiness, group belongingness) and allowing them to have face-to-face (or video conversations) would arguably result in an increase in the social influence processes that we observed in the current investigation.

With respect to the finding that reachability, as manipulated in the current study, did not play a meaningful role in the formation of collective memories, future studies should explore whether a more extreme variation in a network's average reachability might result in convergent collective memories. We note that despite attempting to manipulate reachability in such a way as to keep average reachability equal between the low and high-clustering networks, we still measured a marked difference in reachability between the two types of networks. High clustering networks were characterized by lower average reachability ($M_{Reach.} = 4.81$) than low clustering networks ($M_{Reach.} = 6.10$). This is consistent with existing research in social network formation: the higher the network clustering, the lower the reachability of the network (Borgatti, 2005; Watts & Strogatz, 1998). This difference in reachability could be used, however, to strengthen our conclusion that network clustering might be more important in impacting the formation of collective memories. This is because the high clustering networks experienced significantly larger convergence than the low clustering networks, despite having much lower average reachability. It seems, thus, that the ability to propagate memories between clusters and the subsequent within-cluster rehearsal of information creates conditions that are ripe for the formation of collective memories. We speculate that while reachability likely plays a role in propagating memories, in order for collective memories to be formed a community needs repeated rehearsal of information within-clusters. This rehearsal facilitates the accumulation of information in a shared pool of items that constitute the collective memory of the community. We also note that it is likely that in small networks, such as the ones we employed in the current project, once a moderate level of reachability is attained, reachability no longer produces distinguishable effects, a conjecture in need of testing.

Finally, we note that among the networks we tested, the one that most resembles real-world network configurations (i.e., high reachability and high clustering) was the one that produced maximal mnemonic convergence. Even though more research needs to be conducted to verify the generality of this pattern across different contexts, this finding suggests that (1) naturally-forming human communities seem to be especially well-calibrated to form collective memories and (2) in situations in which network connectivity could be manipulated (e.g., classrooms, organizations), network structure could be used to facilitate either information overlap or information diversity.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jesp.2019.05.001.

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