Social network structure shapes the formation of true and false memories at collective level

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Abstract

Societal structures and theoretical models of memory organization share network-like features, suggesting potential mutual insights into how information spreads and shapes collective memories. Here, we used experimental manipulations of the topological structure in lab-created community networks during a computer-mediated conversational recall task of lists of words from a DRM paradigm to test a central premise from the spreading of activation account in cognitive psychology: the emergence of true and false memories. We hypothesized that social network structure, whether clustered or not, would influence the formation of true and false memories. We found that information exchange promoted true memories in clustered networks by reinforcing the mnemonic convergence of the community members' memories. Conversely, nonclustered networks lead to a greater number of false memories by increasing widespread cross-activation of nonoverlapping memories, blurring the boundaries between true and false memories. Current findings provide empirical evidence that mnemonic spreading within the social network influenced the emergence of true and false memories and highlight the dynamic interplay between network topology, memory dynamics, and collective knowledge evolution, shedding light on memory processes in both individual and social contexts.

Introduction

Human societies are structured as interconnected social networks, fostering the exchange and dissemination of information between directly and indirectly connected individuals and groups. How groups (small or large) share and remember their group's past shapes their collective narratives, traditions, and identity (Hirst et al., 2018; Roediger et al., 2019; Wertsch & Roediger, 2008). Similarly, in cognitive psychology, the notion that memories are built in a network-like structure through which the activation of one node propagates throughout associated nodes constitutes a component in extant theoretical models of memory and cognition (Anderson, 1983; Collins & Loftus, 1975; McClelland & Rumelhart, 1985; Roediger & McDermott, 1995). Memories, much like individuals within a community, are closely linked to the interconnected elements of their network, thereby sharing the possibility of being influenced by the concurrent activation of other network nodes. Hence, an intriguing avenue of inquiry would involve examining the common organizational and propagation properties between societal and memory structures, potentially providing mutual explanatory insights.

One strategy for exploring how social networks and memory interact involves delving into how memories take shape through social communication. Notably, the act of recalling shared experiences in conversation leads to the synchronization of memories among individuals participating in the interaction (Coman et al., 2009; Congleton & Rajaram, 2014; Greeley et al., 2023). As these influences originating at the individual level become integrated into a larger network of social interactions, they contribute to the emergence of collective memories (Coman et al., 2016; Hirst & Echterhoff, 2012; Luhmann & Rajaram, 2015; Yamashiro & Hirst, 2014). Prior investigations have shown that the influence exerted by one individual over another can propagate through the network, affecting the extent to which communities converge on a collective memory of a shared event (Yamashiro & Hirst, 2014). In addition, it is important to note that social interactions not only shape individual memories but also the features of the social network, which, in turn, affect the formation of collective memories within a community. (Hirst et al., 2018; Rajaram & Pereira-Pasarin, 2010; Vlasceanu et al., 2018). For instance, networks characterized by closely interconnected clusters of individuals exhibit a higher likelihood of forming convergent collective memories, whereas networks consisting of sparsely connected clusters tend to show less memory convergence across the members within the community (Coman et al., 2016).

On the other hand, the conceptualization of memories as entities that are built in a network-like structure through which the activation of one node propagates throughout associated nodes offered important insights into the organization and structure of our mental representations and help clarify essential psychological processes that elucidate how novel experiences interplay with our stored memories (Anderson, 1983). For example, in classic semantic priming paradigms (Neely, 1977, 1991), the speed of deciding that a letter string (*doctor*) is a word increases if it has been preceded by an associatively related word (*nurse*) relative to an unrelated word (*house*). The basic explanation is that the activation of *nurse* spreads through an associative-semantic network, thereby partially activating the related word *doctor* so that it can be recognized faster. Nevertheless, if the spreading of activation framework has potential value in memory, then one should be able to find that activation does not simply influence a directly related item but also extends beyond directly related ones to more distant items in memory network. A well-known example that aligns with the notion that the activation of a node spreads across multiple memory network links is provided by the literature on false memories. A common approach to elicit robust false memories at the lab was developed by Roediger & McDermott (1995), based on earlier search by (Deese, 1959), and known as the Deese-Roediger-McDermot (DRM) paradigm. In this design, participants encode a list of words (e.g., *bed, tired, rest, nap, dream, wake, snooze, blanket, yawn, drowsy*) semantically associated to a non-presented critical word (e.g., *sleep*). Although *sleep* has not been presented, the intriguing finding from many experiments is that the critical word is falsely recalled and falsely recognized at very high levels in a subsequent memory test. The spread of activation framework helps explain this phenomenon by proposing that due to the strong associations between the encoded words, the activation of *bed* propagates to activate the concept of *sleep*, even though *sleep* had never been explicitly presented (Meade et al., 2007; Roediger, Watson, et al., 2001; Roediger III et al., 2001). Compelling evidence supporting the spread of activation account of the DRM phenomenon is that false recall increases steadily with increasing number of encoded word associates (Robinson & Roediger III, 1997). Hence, encoding more words boosts the context for activating related concepts, increasing the chances of cross-activation and indicating that activation of a non-presented but related lure item spreads accumulatively across the associated nodes in the memory network for that critical word. Conversely, the encoding of a reduced number of words promotes the strengthening of memory representation of the studied items reducing the propagation to other coactivated words and reducing the emergence of false memories.

The interplay between network modularity or clustering, the process of diffusion, and the formation of true and false memories unveils an intriguing connection with the emergence of collective memories. Network modularity in social communities, characterized by the organization of interconnected nodes into distinct clusters, influences on the propagation of information and the subsequent construction of memories. Communication within clustered community networks promotes localized spread of information, which aids the reinforcement of similar memories among their individuals fostering mnemonic convergence. Conversely, communication in less modular collective networks, where propagation is not constrained by rigid module boundaries between members of the community, information can permeate more sparsely across the entire community network, thereby promoting the coactivation of a broader range of encoded memories at a collective level.

In this study, we aimed on discerning how the formation of both true and false memories might be influenced by the patterns of information exchange among individuals belonging to two distinct social network configurations: a clustered network and a nonclustered network. The central premise of our hypothesis is that the structure of social networks, whether characterized by clustering or lack thereof, plays a pivotal role in shaping the cognitive mechanisms underpinning memory processes (Greeley et al., 2023). We posited that the localized and controlled exchange of information within a clustered network fosters the preservation of accurate memories at individual level. This would be achieved through the reinforcement of related memories within clusters of community members. In contrast, we hypothesized that a nonclustered social network, characterized by more widespread information exchange, may promote the emergence of semantically related false memories. This stems from the propensity of diverse yet interconnected nodes to coactivate less convergent conceptually related memories, resembling the dynamics that promote false memories at cognitive level. Through this approach, we aimed to shed light on the relationship between network modularity, information diffusion, and memory dynamics, ultimately contributing to a deeper understanding of the mechanisms that govern memory formation at collective level. Understanding the connections between cognitive and social networks offers valuable insights into the intricate dynamics that influence both individual and collective memories, thereby deepening our understanding of memory processes across different scales.

We asked 170 healthy individuals to participate in a memory experiment using the online recruitment systems of the University of Barcelona and the University of Granada. Following previous research (Coman et al., 2016), the experiment included 4 phases, each of them conducted with network community groups of 10 participants each that completed them on separate computers (**Figure 1**) (see *Materials and Methods*). In the preconversational study phase (Phase I), each participant encoded 100 words presented in a computer. The stimuli included 10 wordlists from different semantic categories, each of them associated to a non-presented critical lure word (*SI Appendix*). Subsequently, during the preconversational recall phase (Phase II), each participant was asked to individually recall the studied words by typing them in a textbox in their computer. This was followed by the conversational recall phase (Phase III), wherein participants from the 10-member communities engaged in paired conversations with 3 partners, collectively recalling the studied content. These interactions occurred in a chat-like computer-mediated environment where participants typed their responses in a turn-taking manner. Lastly, in the postconversational recall phase (Phase IV), participants individually freely recalled again the initially studied word lists.

In the conversational recall phase, each participant completed 3 conversational free recalls with 3 different group members within the network community, pre-arranged experimentally. They were tasked with collaboratively recollecting as many words as possible from the studied wordlists. Within the clustered condition (n = 80 participants; eight 10-member networks), interactions followed a network structure with two subclusters. Conversely, in the nonclustered condition (n = 90 participants; nine 10-member networks), interactions occurred in a single large cluster. As in Coman et al., (2016) study, the global clustering coefficient, C (Freeman, 1978; Griffiths et al., 2013), contrasted between the clustered condition (C = 0.40) and the nonclustered condition (C = 0.00), thereby setting up an experimental design in which both network conditions were made comparable regarding factors such as the number of participants per network, the sequence of conversational interactions, and each participant's involvement in three conversations within their respective network.

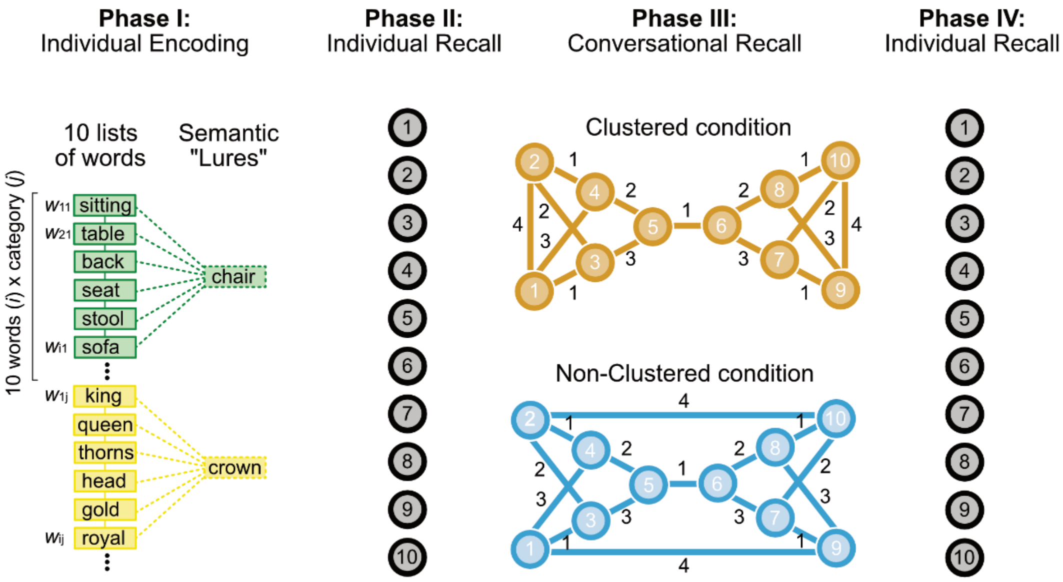

Figure 1. Experimental design. Phases of the experiment involve participants initially learning 10 lists of semantically related words (*Phase I*). In the preconversational (*Phase II*) and postconversational (*Phase IV*) phases, ten participants individually recollect the learned information. The conversational recall phase (*Phase III*) includes participants, indicated by white numbers, in either the clustered (top) or nonclustered (bottom) condition. Participants are depicted as circles, and interactions are represented by links. The order of the sequential conversations between paired participants are indicated by numbers in black.

Results

Social network structure modulates the recall of true and false memories

We first examined whether participants' recall for studied and nonstudied lure words changed after collaborative recall as a function of network type. To assess for this possibility, we calculated the recall rate for studied and critical lures before and after collaborative recall between participants of the clustered and the nonclustered network conditions. This analysis involved quantifying the recall rate for true and false items for each individual before (Phase II) and after (Phase IV) the conversational phase. A mixed factorial ANOVA, with recall type (true vs. false) and time (preconversation vs. postconversation) as within-subjects factors, and network condition (clustered vs. nonclustered) as a between-subject factor, revealed a significant main effect of recall type ($F(1,168) = 23.08$, $p < 0.01$, $\eta^2 = 0.12$) and a main effect of time ($F(1,168) = 149.73$, $p < 0.01$, $\eta^2 = 0.47$) but not a significant interaction recall type x time ($F(1,168) = 0.14$, $p < 0.91$, $\eta^2 < 0.01$). The results indicated that participants recalled, in overall, a greater number of true than lure words during the experiment but that their recall rate increased for both true and lure words in Phase IV when compared to Phase II (*SI Appendix)*. However, we found a non-significant recall type x group ($F(1,168) = 0.31$, $p = 0.58$, $\eta^2 = 0.002$) nor time x group ($F(1,168) = 0.53$, $p = 0.47$, $\eta^2 = 0.003$) or a recall type x time ($F(1,168) < 0.01$, $p = 0.91$, $\eta^2 < 0.001$) interaction but a significant three-way interaction recall type x time x network condition effect ($F(1,168) = 3.93$, $p = 0.049$, $\eta^2 = 0.02$), indicating that the degree of pre-post conversational recall rate differed for true and false memories as a function of network condition (**Figure 2**).

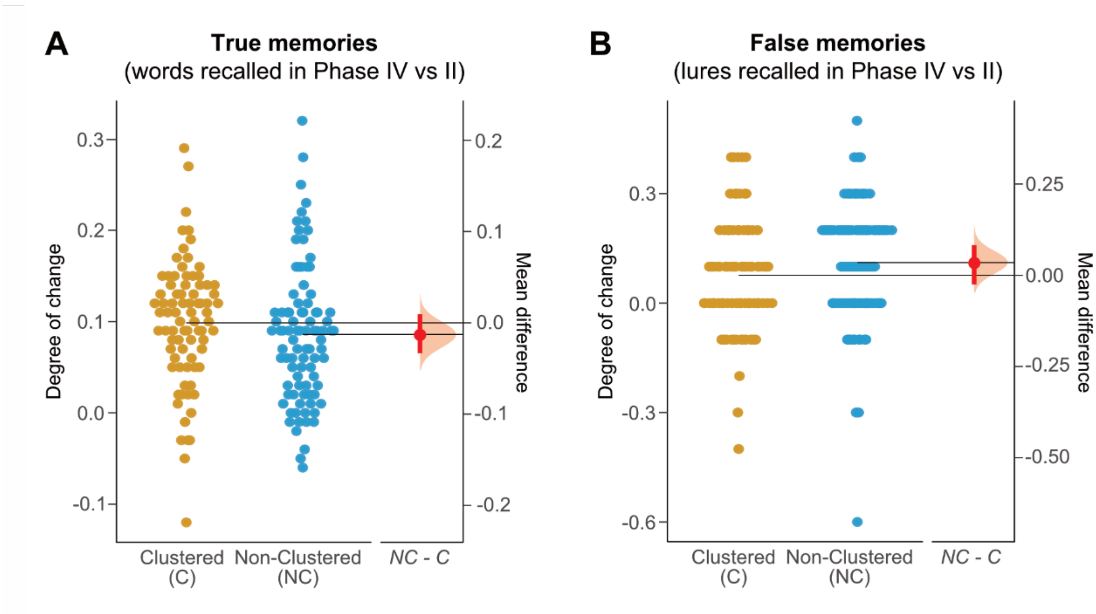

Figure 2. Memory performance in pre and postconversational recall phases. Differences in recall rate of (**A**) true and (**B**) lure words (false memories) in Phase IV compared to Phase II. The mean difference between the clustered and the nonclustered group is shown in this Gardner-Altman estimation plot (Ho et al., 2019). Both groups are plotted on the left axes; the mean difference is plotted on a floating axis on the right as a bootstrap sampling distribution. The mean difference is depicted as a dot; the 95% confidence interval is indicated by the ends of the vertical error bar.

Separate repeated measures ANOVA for true and false memories showed a significant effect of time (True memories: $F(1,168) = 281.44$, $p < 0.01$, $\eta^2 = 0.63$; False memories: $F(1,168) = 55.83$, $p < 0.01$, $\eta^2 = 0.25$) but did not show a significant time x group interaction effect either for true ($F(1,168) = 1.34$, $p = 0.25$, $\eta^2 = 0.01$) or false memories ($F(1,168) = 1.93$, $p = 0.16$, $\eta^2 = 0.01$). However, upon closer examination of the participants' recall differences between phase II and IV we detected outliers within the dataset (defined by those data points that exceeded above the 3rd or below the 1st shape memory brain plus 1.5 times the interquartile range of the data; **Figure 2**). Consequently, we implemented a robust linear regression model to assess for differences between recall phases as this analysis is less sensitive to outliers than

ANOVA (Maechler et al., 2023). We found that true word recall increased to a greater extent in the postconversational phase compared to preconversational recall for members in the clustered condition ($\beta = 0.021$, $SE = 0.011$, $t(168) = 1.929$, $p = 0.053$), whereas the extent of false memories during postconversational recall increased more in the nonclustered condition than in the clustered condition ($\beta = 0.045$, $SE = 0.023$, $t(168) = 1.918$, $p = 0.056$). These results underscore the influence of network type on the recall rates of both true and false memories, with clustered networks enhancing true memory recall in the postconversational phase and nonclustered networks promoting a greater increase in false memories.

To investigate whether these findings where specific to the studied words and the associated lures, we also analyzed memory intrusions of nonrelated words during the two recall phases (clustered group in phase II: M = 7.42%, STD = 8.19% and in phase IV: M = 7.70%, STD = 7.35%; nonclustered group in Phase II: M = 7.87%, STD = 10.62% and in Phase IV: M = 9.17%; STD = 12.39%). A repeated measures ANOVA including phase (II vs IV) as within-subjects factor and network condition (clustered vs. nonclustered) as a between-subjects factor, confirmed that memory intrusions for nonrelated words did not change in either network group before and after the conversational phase (main effect of phase: $F(1,168) = 1.27$, $p = 0.26$, $\eta^2 = 0.08$; phase x network condition interaction effect: $F(1,168) = 0.53$, $p = 0.47$, $\eta^2 = 0.03$). Altogether, these effects were in the hypothesized direction, but only marginally significant; thus, we conducted additional analyses to explore the effect of network structure more precisely on true and false memories.

Dynamics of memory performance during shared recall

We next examined whether the repeated conversations modulated the memory accuracy observed at individual level when comparing pre and postconversation in our previous analysis. To investigate this issue in our data, we first measured the proportion of correctly recalled words and the proportion of lure words recalled in each participant's conversation iteration (1^{st}, 2^{nd} and 3^{rd}) (*SI Appendix*). We implemented a mixed factorial ANOVA that included conversation iteration (1^{st}, 2^{nd} and 3^{rd}) and type of memory (true and false) as within-subjects factors, and network condition (clustered and nonclustered) as a between-subjects factor to assess for statistical effects. This analysis confirmed that, in overall, participants tended to recall more true than false memories (main effect of type: $F(1,168) = 44.16$, $p < 0.001$, $\eta^2 = 0.21$) and that the two types of memories changed throughout conversation iteration (main effect of iteration: $F(2,336) = 6.99$, $p = 0.001$, $\eta^2 = 0.04$). However, we found that the degree of memory change throughout conversation iteration varied for true and false memories as a function of network condition, as indicated by a significant three-way interaction type x iteration x network condition ($F(2,336) = 3.26$, $p = 0.04$, $\eta^2 = 0.02$). A separate ANOVA for true memories indicated that memory accuracy increase throughout the conversational phase iterations (main effect of iteration: $F(2,336) = 9.25$, $p < 0.001$, $\eta^2 = 0.05$) but the increase was similar between members of the two network conditions (network condition x iteration: $F(2,336) = 1.94$, $p = 0.15$, $\eta^2 = 0.01$) (**Figure 3A**). A polynomic contrast confirmed that the memory accuracy increase was linear ($F(1,168) = 14.54$, $p < 0.001$, $\eta^2 = 0.08$). Conversely, the same analysis on false memories indicated more pronounced increase in nonclustered than in clustered condition (main effect of iteration: $F(2,336) = 3.32$, $p = 0.04$, $\eta^2 = 0.02$; network condition x iteration: $F(2,336) = 2.83$, $p = 0.06$, $\eta^2 = 0.02$) (**Figure 3B**). A polynomic contrast confirmed that the interaction of the effects was linear ($F(1,168) = 5.71$, $p = 0.02$, $\eta^2 = 0.03$). Post-hoc contrasts revealed that the rate of false memories was greater in the 2nd ($t(89) = 2.99$, $p = 0.004$; Cohen's $d = 0.31$) and 3rd ($t(89) = 2.98$, $p = 0.004$; Cohen's $d = 0.34$) recall iteration compared with the 1st recall iteration in the nonclustered condition, whereas false memories did not differed significantly between recall iterations in the clustered condition (all $t(79) < 1.5$, $p > 0.1$). Similar trends were found when differences between 1st and 3rd recall performance were analyzed by means of a robust linear regression model (true memories: $\beta = 0.013$, $SE = 0.019$, $t(168) = 0.65$, $p = 0.51$; false memories: $\beta = 0.055$, $SE = 0.029$, $t(168) = 1.91$, $p = 0.05$). These results provide support for the hypothesis that the conversational network structure influences the emergence of false memories.

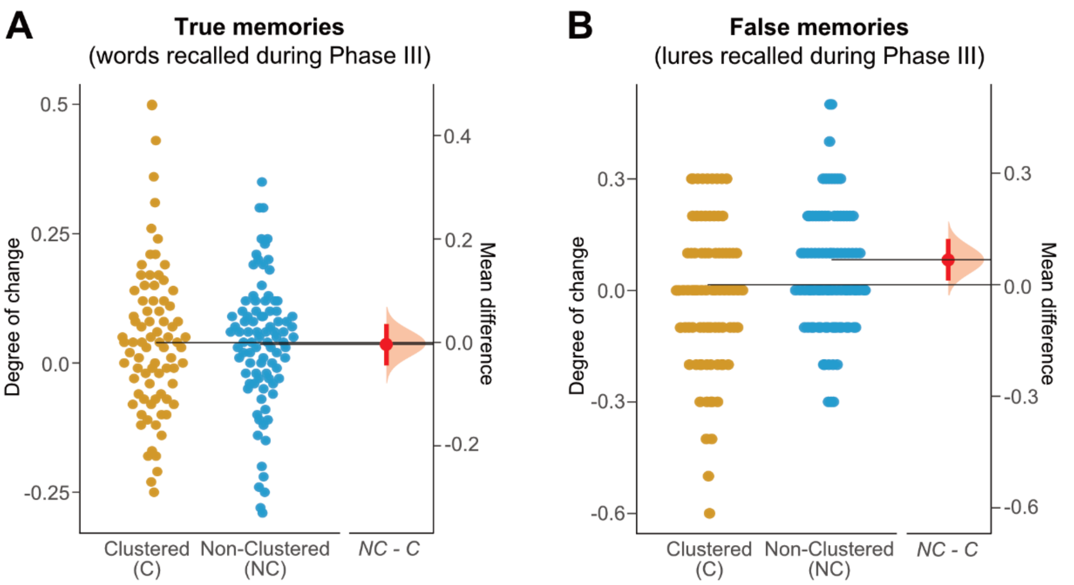

Figure 3. Memory changes during the conversational phase III. Differences in recall rate of (**A**) true and (**B**) lure words (false memories) between the 1st and the 3rd conversational recall in Phase III. The mean difference between the clustered and the nonclustered group is shown in this Gardner-Altman estimation plot (Ho et al., 2019). Both groups are plotted on the left axes; the mean difference is plotted on a floating axis on the right as a bootstrap sampling distribution. The mean difference is depicted as a dot; the 95% confidence interval is indicated by the ends of the vertical error bar.

Memory consistency and network mnemonic convergence

Altogether, our findings indicate that network structure had opposed mnemonic effects on the memory representations of network members and that these effects emerged through an iterative process of shared recall. More specifically, we hypothesized that the localized and controlled exchange of information within a clustered network fosters the preservation of accurate memories at individual level. This would be achieved through the reinforcement of related memories in repeated recall conversations within the members of the community. Conversely, in the nonclustered network conditions, items included in the recall conversational iterations would diverge in a greater proportion, thereby coactivating less convergent related memories among the members of the community and promoting the emergence of false memories. To assess for this possibility, we calculated the degree of memory consistency between 1^{st} and 2^{nd} iterations and between the 2^{nd} and the 3^{rd} iterations for each participant and normalized each of these measures by the total number of correct items recalled in the first recall stage (**Figure 4A**). Confirming our hypothesis, the results of a repeated measures ANOVA including iteration ($1^{st}/2^{nd}$ and $2^{nd}/3^{rd}$) as a within-subjects factor and network condition as a between-subjects factor, revealed a significant iteration x network condition effect ($F(1,168) = 5.98$, $p = 0.01$, $\eta^2 = 0.034$) (**Figure 4B**). A post-hoc analysis comparing memory consistency scores between the $1^{st}/2^{nd}$ and $2^{nd}/3^{rd}$ iterations in the two network groups confirmed that memory preservation increased to a greater extent in the $2^{nd}/3^{rd}$ iteration in the clustered network group compared to the nonclustered group ($t(168) = 2.45$, $p = 0.02$, Cohen's $d = 0.36$). The current results indicate that the communication within members in social networks, whether characterized by clustering or lack thereof, plays a pivotal role in shaping the cognitive mechanisms underpinning memory processes.

In addition, these findings were specific to the studied words and the associated critical lures as both groups showed similar pattern of memory intrusions of nonrelated words during the conversational phase (clustered group: M = 26.04%, STD = 20.05%, M = 28.49%, STD = 20.23% and M = 25.41%, STD = 17.85%, for 1^{st}, 2^{nd} and 3^{rd} iteration respectively; nonclustered group: M = 28.18%, STD = 20.25%, M = 26.72%, STD = 17.37% and M = 25.14%, STD = 18.89%). This was confirmed via a repeated measures ANOVA including iteration and network condition as within and between-subjects factors, respectively (main effect of iteration: $F(2,336) = 1.09$, $p = 0.39$, $\eta^2 = 0.005$; Interaction iteration x network condition effect: $F(2,336) = 0.70$, $p = 0.49$, $\eta^2 = 0.004$).

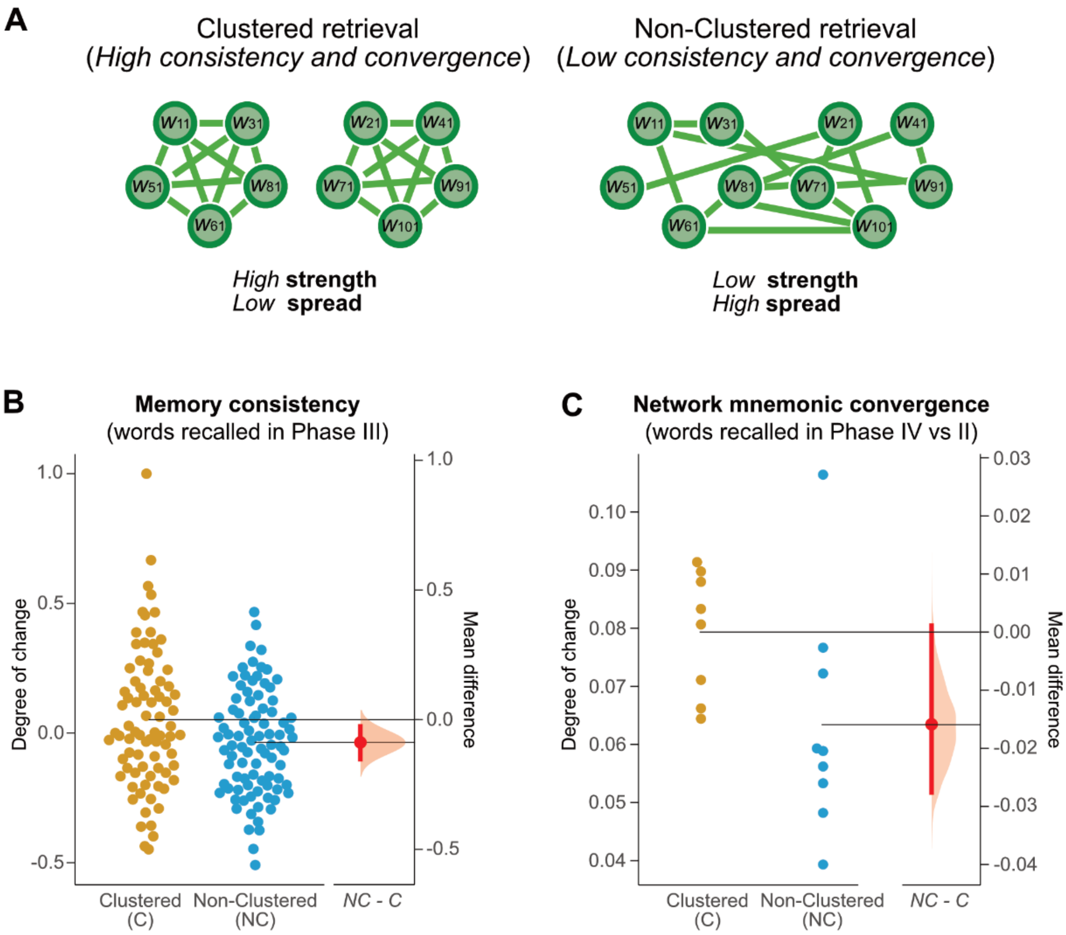

Figure 4. (**A**) A graphic summary of the hypothesis of the study. We suggested that in clustered networks, where information exchange is localized, accurate memories are better preserved due to reinforced related memories within communities (*Left*). In contrast, nonclustered networks with widespread information exchange may lead to related false memories. This is because interconnected nodes can coactivate less convergent conceptually related memories, similar to the cognitive dynamics promoting false memories (Right). (**B**) Changes in the degree of memory consistency of true memories (words) between $1^{st}/2^{nd}$ and $2^{nd}/3^{rd}$ conversational recall iteration (Phase III) for each member of the two network conditions. (**C**) Difference of mnemonic convergence scores for the clustered and nonclustered conditions in Phase IV compared to Phase II. The mean difference between the clustered and the nonclustered group is shown in this Gardner-Altman estimation plot in (B) and (C) (Ho et al., 2019). Both groups are plotted on the left axes; the mean difference is plotted on a floating axis on the right as a bootstrap sampling distribution. The mean difference is depicted as a dot; the 95% confidence interval is indicated by the ends of the vertical error bar.

The fact that clustered network conditions preserved memory for true memories may indicate that individuals within the clustered condition tended to converge in greater extend at network level after the conversational phase. To account for this possibility, we calculated a mnemonic similarity score for true and false memories for each pair of participants in the network by adding the number of items remembered in common by both participants, and then dividing this sum by the total number of items recalled. Then, following Coman et al. (2016), a network mnemonic convergence score was calculated by averaging the mnemonic similarity scores among all the pairs of participants in the network, separately for the pre and postconversational recalls. We found that, in overall, network mnemonic convergence was higher for true than for false memories (main effect of type: $F(1,15) = 484.54$, $p < 0.001$, $\eta^2 = 0.97$). We also found that the degree of mnemonic convergence increased after conversational recalls (main effect of recall phase: $F(1,15) = 331.34$, $p < 0.001$, $\eta^2 = 0.96$) and that this change differed between true than false memories (type x pre effect: $F(1,15) = 213.34$, $p < 0.01$, $\eta^2 = 0.93$). However, we also found a significant type x recall phase x network condition interaction effect ($F(1,15) = 4.71$, $p = 0.046$, $\eta^2 = 0.24$), indicating that the change between pre and postconversational mnemonic convergence for true and false memories differed between network conditions.

A separate repeated measures ANOVA for network mnemonic convergence for true and false memories allowed identifying the source of the three-way interaction. More specifically, the ANOVA including recall phase (i.e., pre and postconversation) and network condition suggested that mnemonic convergence for true items increased more in the clustered than in the nonclustered network condition (main pre-post effect: $F(1,15) = 331.23$, $p < 0.01$, $\eta^2 = 0.96$; network condition x pre-post interaction effect: $F(1,15) = 4.12$, $p = 0.06$, $\eta^2 = 0.22$). Similar results were found when differences in mnemonic convergence between pre and postconversational recall were analyzed with a robust regression model that controlled for outliers in the data (true memories: $\beta = 0.02$, $SE = 0.01$, $t(168) = 2.35$, $p = 0.03$) (**Figure 4C**). Conversely, similar increase was found in the clustered and in the nonclustered groups regarding the mnemonic convergence for lure items (main pre-post effect: $F(1,15) = 10.42$, $p < 0.01$, $\eta^2 = 0.41$; network condition x pre-post interaction effect: $F(1,15) = 0.82$, $p = 0.38$, $\eta^2 = 0.05$). Taken together, our findings suggest that a factor influencing the emergence of false memories may be the alteration in the spread and strength of information within social networks.

Discussion

Our study sheds light on the significant influence of network clustering in shaping true and false memories at a collective level. Our findings illustrate that clustered networks have a beneficial influence on memory retention, reducing the scattering of information intended for memorization. This effect is instrumental in enhancing the accuracy and fidelity of stored memories, as the clustered topology facilitates the containment of closely related nodes that reinforce each other's nodes, leading to a more consistent memory representation. In contrast, the dynamics within nonclustered networks exhibited the increased cross-activation of loosely related nodes, blurring the boundaries between items and contributing to the formation of false memories.

Our findings align with previous studies that showed that conversational remembering is selective (Marsh, 2007; Rajaram & Pereira-Pasarin, 2010), susceptible to errors (Schacter, 2022), capable of altering the memories of the interlocutors (Hirst & Echterhoff, 2012) and shaped by the degree of clustering network of the community structure (Coman et al., 2016). They also align with the notion that these effects can be explained by cognitive processes that take place during collaborative recall, such as memory reinforcement (Roediger et al., 2009) and social contagion (Maswood & Rajaram, 2019; Meade & Roediger, 2009; Roediger, Meade, et al., 2001). What distinguishes the current study from prior research is that it explored the potential that a general information transmission principle, based on the modularity of a network structure, could elucidate the nature of how memories are represented at the cognitive level. Specifically, collective memories are believed to arise from the exchange of information among engaged members of a community, with influence indirectly transmitted through connected peers (Yamashiro & Hirst, 2014). Cognitive models explaining memory representation suggest that a comparable process underlies the interconnection of memories sharing common content, facilitating the development of abstract and semantic-based representations (McClelland et al., 2020). The current findings demonstrate, for the first time, that a shared network information transmission principle can have an impact at both social and at the individual level.

Our results highlight the dynamic nature of memory, where information is actively reconstructed and reorganized by the brain. This is consistent with the notion that memories are stored and retrieved through interconnected neural networks in the brain and false memories would occur when these networks overlap during recall, distorting recollections (Kurkela & Dennis, 2016; Wing et al., 2020; Ye et al., 2016). However, while neuroimaging-supported empirical studies (e.g., Chadwick et al., 2016) provide valuable evidence supporting the role of mnemonic neural network activation in the brain, there are persisting limitations in our ability to mechanistically examine and precisely capture the correspondence of memory representations at the neuronal level. Our research contributes to this field by leveraging the analogy that these interconnected memory networks can be likened to a social network, where each node represents a community member engaged in dynamic interactions. This analogy provides a novel perspective, demonstrating empirically that memories are indeed significantly influenced by the cross-coactivation of associated nodes. In doing so, our study advances our understanding of the complex interplay between cognition and social networks, opening new avenues for research in this multidisciplinary field.

It is important to acknowledge that even though our study isolated the effects on true and false memories associated to network structure, these effects assumed that all individual members of the community and their impact at the network-wide level are of equal significance. However, not all individual members possess equal potential to influence the network's collective memory. For instance, individuals who connect between clusters have a significant influence in the network (Derex & Boyd, 2016), especially if they shared recall takes place at early stages of other dyadic-level conversations within the network community (Momennejad et al., 2019). Interpersonal factors, such as source credibility (partners vs. strangers) (French et al., 2008), perception of power (influential vs. weak) (Skagerberg & Wright, 2009) and confidence (competitive vs. cooperative) (Wright et al., 2008) (see for a review, Maswood and Rajaram, 2019) influences social contagion and likely the emergence of false memories. Thus, systematic manipulations involving different temporal arrangements of shared conversations within members within the network topology and the inclusion of relationship characteristics of the members of the community will likely reveal meaningful network dynamics involving the formation of true and false collective memories.

The impact of information transmission within social communities is an important topic of research as it reaches a large-scale societal impact, from attitudes and beliefs (Hirst & Echterhoff, 2012) and to political polarization (Bakshy et al., 2015), and collective behavior (Bahrami et al., 2012). The strategic dissemination of information within societal communities has also been a subject of crucial debate, with ramifications for political (Frenda et al., 2013) and health-related attitudes (Centola, 2010). One concerning aspect is the potential for these strategies to inadvertently foster false beliefs, which is a pervasive issue in society. Mitigating the emergence of false beliefs in the society is challenging, because attitude-congruent false events promote feelings of recognition and familiarity, which in turn interfere with source attributions (Johnson et al., 1993). Our research suggests that one possible effective strategy to address this problem may involve structuring dissemination efforts based on the social communication network's design by controlling the spread of information within distinct communities rather than disseminating it haphazardly through social networks or large-scale media channels.

While it is tempting to conclude that false memories point to fundamental flaws in the nature or composition of memory, there is a growing number of researchers who argue that, to the contrary, false memories reflect the operation of adaptive processes as they reflect gist-based processing supporting the retention of themes and meanings that facilitate generalization and abstraction (Gallo, 2010; Roediger & McDermott, 1995; Schacter et al., 2011). Individual differences in the generation false memories are also associated to divergent – the processes of generating multiple alternative ideas or solutions (Thakral et al., 2021) - and convergent thinking - selecting the creative ones (Dewhurst et al., 2011), two core components associated to creative thought (Ward et al., 1997). Creativity plays a major role in human development as it is thought to fundamentally distinguish human beings from other branches of the tree of life (Runco & Albert, 2010), becoming and important focus of school curricula across the world (Patston et al., 2021). Unfortunately, training on creativity performance in formal educational settings is still a challenging endeavor (DeHaan, 2011) and could benefit from the approach proposed herein by, for example, promoting nonclustered exchange of information among individuals in classrooms.

The duality between clustered and nonclustered network effects observed in the current study prompts an intriguing exploration into the trade-offs between memory accuracy and the potential for creative reinterpretations at the collective level (e.g., Rajaram, 2011). The clustered architecture may seem particularly suited for contexts where the preservation of detailed information is paramount, such as historical or personal events. On the other hand, the nonclustered arrangement's propensity for semantic spreading highlights its potential role in promoting conceptual blending and fostering innovative interpretations. In a broader context, our findings underscore the intricate interplay between network topology, memory dynamics, and the construction of collective memories. This not only enriches our understanding of the cognitive processes underlying memory but also provides a lens through which we can examine the intricate relationships between social network structure, memory representation, and the evolution of collective knowledge.

Materials and Methods

Participants

Following previous studies using similar experimental design, we aimed at recruiting 10 groups of 10 participants each for each experimental condition. The statistical power afforded by this sample size was deemed adequate given effect sizes obtained in previous studies using a similar sample size and experimental paradigm (Coman et al., 2016; Vlasceanu et al., 2020). However, due to technical problems with the need to run the experiment synchronically within groups of 10 people, the final sample included in the study consisted of 170 healthy participants (78.2% females) with a mean age of 24.7 (SD = 7.3). All participants were native or highly proficient Spanish speakers. The study was advertised on a platform for students affiliated with the University of Barcelona or the University of Granada. Additionally, flyers of the study were posted around the university campuses and shared on social media. The participants were self-selected and received either 2 course credits or 5 euros as compensation. For each group of 10 participants, an additional prize draw of 20 euros was conducted. Informed consent was obtained upon familiarization with the experimental procedure before the experiment onset. The study was approved by the University of Barcelona Ethics Committee.

Materials

The DRM paradigm was used to collect data in the present study. Ten DRM word lists used in the paradigm were adopted from Alonso et al. (2004) and attached in *SI Appendix*. Each of the lists contained 10 words semantically related to a critical non-presented word – a lure. For example, (translated from Spanish) *wind, breathe, fresh* etc. were the presented words associated with the critical non-presented word *air*. The distractor task consisted of 36 arithmetical problems (e.g., (12 / 4) + 4 = 7) with a 'yes' or 'no' answer, each presented for 5 seconds. The experimental task was programmed using the Qualtrics platform (Qualtrics.com), specifically its branch SMARTRIQS (smartriqs.com) which allows for programming interactive online experiments.

Design and Procedure

The task was completed in synchrony in groups of 10 individuals via a computer. The participants completed it either on-site in the university computer room or remotely. Participants who were physically present at the task were seated at individual computers within a spacious room. They were not provided with information regarding which among the potential others were also engaged in the same task. Participants received full instructions in person or via Google Meets, then they provided the consent form and then they started the task.

Following Coman et al. (2016) study, we defined two network structures - clustered and nonclustered, each of them including 10 participants. In the nonclustered condition, the participants were equally connected to all the individuals in the network.

In the clustered condition, the network was split into two subclusters of 5 individuals which were connected by only one individual from each cluster. In the nonclustered condition, individuals were connected in unconstrained manner to other individuals of the network. Individuals performed the task in their own computers and interacted with each associated member in the conversational phase via the chat box that appeared during the conversational phase in each of their computers. Participants knew that 10 other individuals were concurrently engaged in the task, but they had no direct interaction with anyone except during the conversational phase when using their own computers.

The task started with an encoding phase, followed by a distractor task. In the encoding phase, the participants were asked to memorize words presented on the screen for 2 seconds each. The order of the DRM word lists was random for each participant but the order of words within each DRM list was kept constant. In the distractor task, the participants were asked to indicate whether the arithmetical problem solution was correct or incorrect by clicking the corresponding button. After completing the distractor task, the experiment continued with 3 distinct recall phases: a preconversational individual recall, followed by a conversational recall and a postconversational individual recall. The participants automatically entered the preconversational individual recall phase after finishing the distractor task. They were asked to type down all the words they remembered from the encoding phase for a maximum of 6 minutes. Subsequently, in the conversational phase, each participant was automatically paired and connected with another participant. Each participant completed 3 conversational recalls with 3 different group members. The pairs of participants entered a chat window shown in their individual computers where they were asked to recall words in collaboration by taking turns, as false recall was greater in turn-taking groups compared to both the free-for-all and nominal groups (Basden et al., 1997; Meade & Roediger, 2009; Thorley & Dewhurst, 2007) and when individuals are allowed to free-flowing collaboration (Barber et al., 2010). Each pair member recalled one word at a time in their own computer and subsequently waited for the other pair member to recall and share their word. In case they could not remember a word, they had the option to skip the turn by writing 'pass' in the chat. In this phase, the groups of 10 were organized either into the clustered or nonclustered network. The total time of each conversation was 5 minutes. After the chat, the participants entered the postconversational recall phase which was identical to the first individual recall phase. The total duration of the experiment was approximately 45 minutes.

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SI Appendix

List 1	*List 2*	*List 3*	*List 4*	*List 5*
<u>noche</u>	<u>humo</u>	<u>aire</u>	<u>silla</u>	<u>corona</u>
día	fuego	viento	sentarse	rey
luna	cigarro	respirar	mesa	reina
oscuridad	chimenea	fresco	respaldo	espinas
estrellas	tabaco	oxígeno	asiento	cabeza
negra	gris	puro	taburete	oro
dormir	incendio	vuelo	sillón	diamantes
luz	fumar	libre	mecedora	real
sueño	señal	tierra	sofa	princesa
cielo	olor	gas	madera	poder
fiesta	leña	avión	comodidad	laurel

List 6	*List 7*	*List 8*	*List 9*	*List 10*
<u>hambre</u>	<u>cárcel</u>	<u>caja</u>	<u>guerra</u>	<u>corazón</u>
sed	rejas	guardar	paz	amor
comida	prisión	dinero	muerte	latido
pobreza	preso	fuerte	lucha	rojo
pan	barrotes	sorpresa	horror	sangre
necesidad	cerrado	cartón	odio	vida
miseria	ladrón	secreto	violencia	partido
frío	hierro	cajón	destrucción	roto
alimento	encierro	regalo	fusil	órgano
inanición	celda	herramientas	mal	león
estómago	retener	cuadrada	batalla	alma

Table 1. Lists of the words and the associated <u>lure word</u> included in the study.

	Phase II		Phase IV	
	True	False	True	False
clustered	27.65 (*11.14*)	22.25 (*19.03*)	37.51 (*11.13*)	29.87 (*19.97*)
nonclustered	28.81 (*12.97*)	19.33 (*16.68*)	37.40 (*14.11*)	30.44 (*17.79*)

Table 2. Percentage of true and lure words recalled in Phase II and in Phase IV for each network group. Values indicate means and standard deviation in parenthesis.

	True memories			False memories		
	1st	2nd	3rd	1st	2nd	3rd
clustered	27.41 (*12.31*)	28.56 (*12.00*)	31.40 (*12.43*)	21.50 (*18.36*)	23.25 (*19.08*)	20.00 (*16.99*)
nonclustered	25.72 (*10.06*)	29.86 (*9.50*)	29.44 (*10.24*)	18.33 (*13.92*)	23.89 (*15.84*)	23.56 (*16.51*)

Table 3. Percentage of true and lure words recalled in each conversational iteration in Phase III for each network group. Values indicate means and standard deviation in parenthesis.