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Group Typology Shapes Social Network Representations

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Abstract

Efficiently representing social networks is challenging, but cognitive schemas can help address this challenge. This study examined whether network schemas related to group typology influence social network representations. In Experiment 1, participants, who were given only group-type information and the number of relationships without network structure, freely constructed friendship networks, forming more interconnected and centralized structures for task groups than social categories. Experiment 2 provided identical partial friendship network data across group types, yet group-type labels biased participants' inferences about potential future friendships, producing network structures similar to those in Experiment 1. In Experiment 3, participants who memorized friendships from social networks—either from a task group or social category—showed greater accuracy when the memorized network structure aligned with the group type that activated corresponding schemas. These results suggest that individuals utilize group-related schemas to represent social networks, with task groups having closer and more centralized connections than social categories do.

Keywords

group typology, task group, social category, social network representation, cognitive schema

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Introduction

Humans engage with others as one of the primary activities of daily life, and the resulting interpersonal relationships play a crucial role in the evolution of cooperative behaviors (De Dreu et al., 2024). To effectively navigate a world that is full of social connections, individuals need to track not only their own social relationships but also the patterns of relationships between others (Bayer et al., 2020; Peer et al., 2019). However, since these relationships are intertwined, forming complex social networks, efficiently representing or tracking information about others' relationships—such as who knows whom or who has friendships with whom—presents a significant cognitive challenge (Basyouni & Parkinson, 2022). Therefore, addressing how interpersonal relationships within social networks can be represented is crucial for understanding human social abilities.

People are naturally attuned to dyadic interpersonal relationships formed through social interactions, and they possess a remarkable ability to track these relationships (Papeo et al., 2019; Tatone & Csibra, 2024). Individuals are often remembered through their relational ties with others (Smith et al., 2020), and their dyadic relationships are organized into cohesive units (Vestner et al., 2019; Yin et al., 2022). Consequently, the most fundamental way of representing interpersonal relationships involves mapping these dyadic connections, such as indicating whether a friendship exists between individual A and individual B and tracking pairs of individuals within social networks (Halford et al., 2010). However, relying primarily on dyadic relationship representations can lead to inefficiencies and increased cognitive load, especially as the number of individuals being tracked increases, making it exponentially more difficult for the brain to manage (Basyouni & Parkinson, 2022; Janicik & Larrick, 2005). For example, tracking relationships among 10 individuals requires the memorization of up to 45 unique dyadic connections. As the group size increases, the memory demands grow exponentially, following the formula $N(N-1)/2$, where N is the number of individuals. This approach also fails to support the inference of higher-level social relationship information, such as understanding the position and status of an individual within the community formed by these people (Brass, 2022;

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Weaverdyck & Parkinson, 2018). Importantly, dyadic ties do not exist in isolation. Humans live in large, complex social environments in which each individual is socially connected to many other individuals, forming larger networks of interpersonal relationships (Smith et al., 2020). Therefore, social network approaches offer a more comprehensive framework for studying how people represent these complex relationship patterns (Basyouni & Parkinson, 2022; Son et al., 2021). In this framework, dyadic relationship representations are structured into larger social networks, in which each node represents a person and each edge represents an interpersonal relationship between two people (e.g., a friendship).

Effectively representing social networks remains a challenging task. Capturing all possible connections between individuals by collecting their discrete relationships can be overwhelming due to information availability limitations. Thus, beyond perceiving dyadic ties, people must integrate these relationships into broader social structures. By providing mental frameworks that shape how social relationships are typically organized within a network, cognitive network schemas help address this challenge (Basyouni & Parkinson, 2022; Flynn et al., 2010; Janicik & Larrick, 2005). These schemas influence how people mentally structure and interpret social networks, affecting their perceptions of connectivity and overall network organization (Brands, 2013). For example, the balance schema, which assumes that friendship relations are transitive, is helpful for supplementing individual ties (Crockett, 1982; Krackhardt & Kilduff, 1999). If person A is friends with person B and B is friends with person C, we tend to assume that A is also friends with C—a concept known as triadic closure. Brashears (2013) further distinguishes between structural schemas, which are derived from inherent patterns within social networks (such as triadic closure), and cultural schemas, which are informed by cultural expectations (e.g., kinship systems). His research indicates that adults can remember a greater number of relationships in more detail when a network aligns with these schemas. Social network schemas, which apply prior knowledge to organize relational information, can help individuals learn about unfamiliar, incomplete networks (Janicik & Larrick, 2005) but may lead them to perceive social contacts as interconnected when they are not (Flynn et al., 2010). Thus, cognitive schemas serve as compression heuristics, enabling the management of large and complex social networks despite limited cognitive resources.

Previous research on network schemas has focused primarily on the local aspects of networks—how dyadic relationships are interconnected in the local network—such as triadic closure (Basyouni & Parkinson, 2022; Flynn et al., 2010; Janicik & Larrick, 2005). However, social networks do more than represent local interpersonal ties; they also provide the structural foundation for social groups. Less attention has been given to global group-level schemas—mental frameworks that shape how social networks are structured within different group contexts—despite their crucial role in social group representation. Social groups are diverse and can be classified into four basic types: intimacy groups (e.g., families and friends, which are highly important and interactive), task groups (e.g., work teams, where individuals share common goals and must work together), social categories (e.g., groups defined by gender or race), and loosely associated groups (e.g., people waiting at a bus stop; Lickel et al., 2000, 2001). This typology reflects not only the categorization of groups but also the cognitive structures that perceivers use to process and store information. Hence, the group type can offer group-related schemas that people use to represent social networks, meaning that people may hold distinct cognitive network schemas for different group types. Unlike intimacy groups, where familial and kinship ties are deeply intertwined and relationships tend to remain stable over time, and loosely associated groups, which often lack strong interpersonal connections, individuals have greater flexibility in defining relationships within task groups and social categories. This flexibility makes cognitive schemas about these groups particularly valuable for exploration. Therefore, the present study focused primarily on comparing social network representations of task groups and social categories.[1] Social categories are primarily formed around shared identities and fulfill needs for affiliation and belonging. In contrast, task groups are characterized by a shared goal and frequent interaction among members who must collaborate to achieve collective goals (Johnson et al., 2006; Lickel et al., 2006). Thus, individuals may perceive interpersonal relationships within task groups as being closer-knit than those in social categories, with central persons facilitating coordination and relationships within a group. Given the emphasis on friend connections in shaping social networks (De Dreu et al., 2024), this study centers on friendship representations and hypothesizes that people's representations of social networks for task groups show more closely connected friend relationships and a greater likelihood of centralization than those for social categories do. In this context, similar to previous studies (Son et al., 2023; 2024), "friendship" refers specifically to an interpersonal bond between two individuals, defined by a concrete, mutual connection as friends.

To test this hypothesis, we conducted three experiments. In Experiment 1, participants inferred the arrangement of a set number of friendships on the basis solely of group labels identified for task groups and social categories in pilot experiments. In Experiment 2, the participants were provided an initial social network with partial network data and were asked to infer the structure of new potential friendships. Experiment 3 required participants to memorize relationship pairs from social networks derived from the generated networks of different group types in Experiment 1. If social network representation relies on group-related schemas because cognitive schemas facilitate memory encoding and retrieval (Brashears 2013; Sweller, 1988, 2011), memory performance should improve when the structure of the learned network aligns with the network schema activated by the corresponding group type.

Experiment 1: Generating Social Networks

To obtain labels for different group types, we conducted pilot experiments in which participants nominated and rated group labels across various dimensions and sorted them into different group types. From this, we identified typical labels for task groups (e.g., "coworkers" and "students working on group assignments") and social categories (e.g., "teachers" and "civil servants"). In the main experiment, we presented these labels to examine how group types influence social network representations. The participants inferred potential relationships among 10 group members on the basis solely of the presented group labels for each group type, associated with a specific number of friendships. We measured the resulting social networks via metrics such as average shortest path length and degree centralization, as these two metrics are essential for capturing distinct structural properties of social networks and differentiating between the network structures of task groups and those of social categories. The average shortest path length measures how closely connected the network is; a lower value indicates that individuals in the network are more closely linked (Boguñá et al., 2020; Newman, 2010; Scott & Carrington, 2011). Degree centralization assesses how concentrated the network is around specific individuals; a higher degree centralization value indicates a network with prominent central persons (Bernstein et al., 2020; Freeman, 1978). On the basis of our hypothesis, the social networks in task groups should exhibit a shorter average shortest path length (i.e., members are more closely connected) and a greater degree centralization (i.e., a greater likelihood of centralized structures) than those in social categories.

Methods

Transparency and Openness. We followed Journal Article Reporting Standards (JARS) and reported how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study (Kazak, 2018). All experiments were approved by the Research Ethics Board of the Department of Psychology at Ningbo University and were conducted in accordance with relevant guidelines and regulations. All data and analysis codes have been made publicly available on the Open Science Framework (OSF) and can be accessed at https://osf.io/2cwmu. Experiments 1 and 2 were not preregistered. However, Experiment 3 was preregistered and can be accessed at https://doi.org/10.17605/OSF.IO/H3W8K.

Participants. Based on the experimental design of this study (a within-subject design with one factor), assuming a conventional medium effect size of $f = 0.20$, an alpha level of .05, and a power of .80, the minimum sample size needed was determined to be 36. Considering the counterbalancing of the experimental materials, which involved a total of eight versions, and to ensure that each version had an equal number of participants, the planned number of valid participants was set at 40. Initially, 42 participants were recruited for this study. However, data from one participant were lost due to program issues, and another participant failed to pass the attention check task. Consequently, a total of 40 individuals (20 men and 20 women) with a mean age of 20.78 years ($SD = 2.30$) participated in this experiment. Each participant received approximately 20 RMB as compensation upon completing the experiment. All the participants were of Han ethnicity, which is the predominant ethnic group in China.

Apparatus and Stimuli. The stimuli were displayed on a 14-inch LED monitor with a resolution of $1{,}920 \times 1{,}080$ pixels and a refresh rate of 60 Hz, positioned at a viewing distance of 60 cm from the participants. Python 3.9 (Python Software Foundation) was used to present the stimuli.

In the pilot experiment (please see the pilot experiment in the Supplemental Material), we first asked participants to nominate and rate group labels in different dimensions for different group types and to sort these labels into various categories. On the basis of the nomination and clustering results, the four most commonly mentioned labels were selected for each group type. Specifically, for the task group type, the selected labels were "coworkers," "students working on group assignments," "game teammates," and "members of a university club." For the social category type, the chosen labels were "teachers," "civil servants," "members of the same political party," and "doctors." The entitativity rated in the pilot experiment was greater for social categories ($M = 6.94$, $SE = 0.14$) than for task groups ($M = 6.18$, $SE = 0.16$; $t(78) = 4.02$, $p < .001$, Cohen's $d = 0.45$, 95% CI [0.22, 0.68]).

Procedure and Design. The experimental procedure was adapted from a previous study (Flynn et al., 2010). The participants first read the instructions on how to complete the experiment (please see the Supplemental Material) for at least 30 s. After reading the instructions, the participants initiated the experiment by pressing the space key. They were then asked to infer potential friend connections among the described group members. During this phase (see Figure 1), the label for a group type appeared at the top of the screen, and participants were informed that there were 10 persons in this group, each assigned a number for identification, with 12 pairs of friends among them. Illustrations of the 10 people were displayed below the instructions. The participants were required to drag all 10 figures displayed on the screen to the panel area and use lines to connect two figures that were friends. Specifically, the left mouse button was used to click on the first figure, and the right mouse button was used to click on the second figure to establish a line. Double-clicking on the line deleted it. The participants could adjust the positions of the figures and refine the connections between group

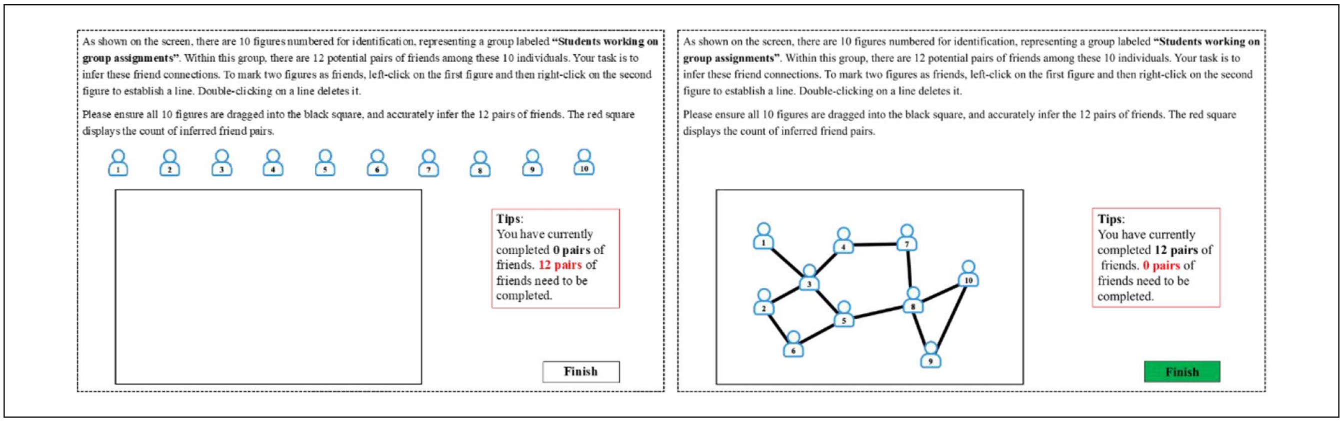

Figure 1. Interface for generating social networks at the start of the task (left panel) and after task completion (right panel).

members. Once they were satisfied with their adjustments, they clicked the "Finish" button to proceed to the next trial.

Eight group labels were presented, with each group type (task group or social category) having four labels. The presentation order was counterbalanced across participants using a Latin square design, resulting in eight versions. Before the formal experiment, the participants engaged in a practice trial to familiarize themselves with the task. In this trial, they were presented with a group labeled "people in a tour group," defined by the pilot experiment as a loose association group. The entire experiment lasted approximately 30 min.

After completing the experiment, the participants were required to perform an attention check task to ensure that they had paid attention to the group labels displayed at the top of the screen. The specific question presented was "Please carefully recall the group labels presented in the experiment and select all (8) of the group labels you saw in the experiment from the following options: A. Students working on group assignments together; B. Lawyers; C. Members of a professional sports team; D. Civil servants; E. Teachers; F. Game teammates; G. Members of the same political party; H. Members of a university club; I. Coworkers; J. Doctors; K. Team members for a contest; L. Believers of a religion." If participants did not pass this check question, they would be excluded.

Analysis. The independent variables were the average shortest path length and degree centralization of the social networks generated by the participants. The average shortest path length assesses the level of separation between nodes (i.e., persons) in the social network. A smaller value indicates a closer social network connection (Boguñá et al., 2021; Newman, 2010; Scott & Carrington, 2014). The degree centralization measures the extent to which the social network is concentrated around specific nodes. A higher degree centralization value suggests a greater likelihood of central persons being present in the social network (Bernstein et al., 2022; Freeman, 1979).

The data were analyzed using R version 4.1.2 (R Core Team, 2023), with the libraries igraph (version 1.4.2) (Csardi & Nepusz, 2006), bruceR (version 2024.6) (Bao, 2025), and ggplot2 (version 3.4.2) (Wickham, 2016). First, the average shortest path length (L) and degree centralization (C) were computed for all eight social networks separately. The average shortest path length is calculated as follows:

$$L = \frac{1}{n(n-1)} \sum_{i \neq j} \mathrm{d}(i, j)$$

where n is the total number of nodes and where $\mathrm{d}(i, j)$ represents the shortest path length from node i to node j.

The degree centralization was calculated as follows:

$$C = \frac{\sum_{i=1}^{n} (C_{\max} - C_i)}{n(n-1)}$$

where $C_{\max}$ is the highest individual degree in the network, C_i represents the degree of each individual, and n is the total number of nodes.

Second, the mean values of the average shortest path length and degree centralization of the social networks were computed separately for task groups and social categories. These mean values served as the dependent variables for subsequent statistical analysis.

Results

The results, depicted in Figure 2, indicated that the average shortest path length of social networks in task groups (M = 2.130, SE = 0.041) was significantly lower than that in social categories (M = 2.274, SE = 0.044; $t(39) = -2.96$, p = .005, Cohen's d = −0.47, 95% CI [−0.79, −0.15]). This result suggests that the social networks in task groups generated by participants exhibit closer connections than those in social categories. Figure 2 also shows that the degree centralization of social networks in task groups (M = 0.253, SE = 0.016) was significantly greater than that in social categories (M = 0.203, SE = 0.012; $t(39) = 2.72$, p = .010,

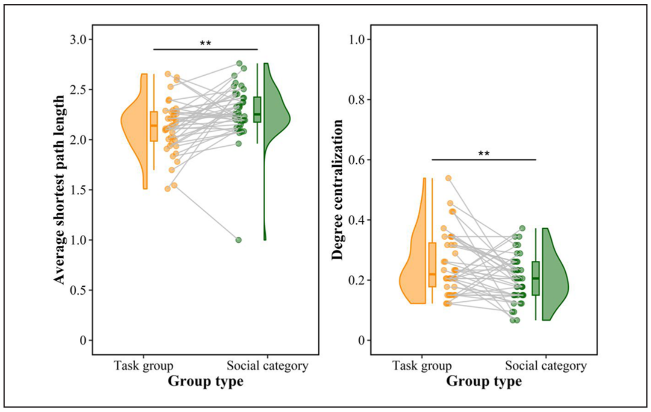

Figure 2. Average shortest path length and degree centralization for different group types in Experiment 1 with the sample of students on campus.

Note. Left: the average shortest path length of social networks in task groups was significantly lower than that in social categories. Right: the degree centralization of social networks in task groups was significantly greater than that in social categories.

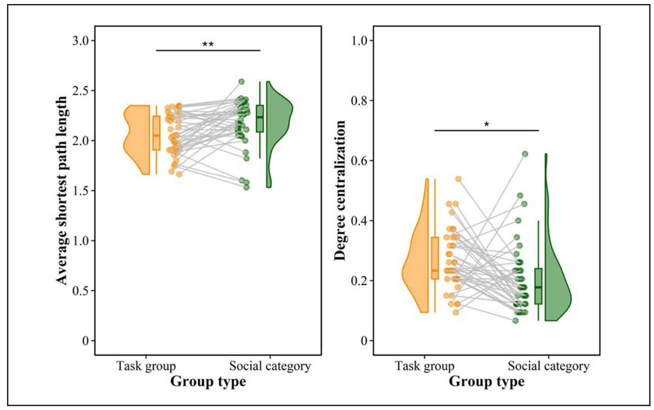

Figure 3. Average shortest path length and degree centralization for different group types in Experiment 1 with the sample of adults off campus.

Note. Left: the average shortest path length of social networks in task groups was significantly lower than that in social categories. Right: the degree centralization of social networks in task groups was significantly greater than that in social categories.

Cohen's d = 0.43, [0.11, 0.75]). Hence, compared with social categories, task groups are more likely to have central persons in their social networks.

Adults Off Campus

The above results were found for participants recruited from a campus setting and may be specific to individuals who do not typically work as a group for a common goal. Hence, we recruited a new group of participants from outside the campus who had experience working as a group and found similar results. A total of 40 participants (21 men and 19 women) with a mean age of 28.05 years (SD = 6.82) participated in this experiment. Among them, 5 people had a junior middle school education, 20 had a senior middle school education, 14 had an undergraduate degree, and 1 had a postgraduate degree. Each participant received approximately 20 RMB as compensation upon completing the experiment.

The results are depicted in Figure 3. The average shortest path length of social networks in task groups (M = 2.060, SE = 0.032) was significantly lower than that in social categories (M = 2.180, SE = 0.037; $t(39) = -2.88$, p = .007, Cohen's $d = -0.46$, 95% CI [−0.77, −0.14]). This experiment replicates the results from college students, suggesting that when only the number—but not the arrangement—of social connections is provided, the generated social networks for task groups have closer connections than those in social categories do. Similarly, Figure 3 also shows that the degree centralization of social networks in task groups (M = 0.267, SE = 0.016) was significantly greater than that in social categories (M = 0.207, SE = 0.019; $t(39)$ = 2.292, p = .027, Cohen's d = 0.36, [0.04, 0.68]). Compared with social categories, the participants believed that task groups are more likely to have central persons in their social networks.

Experiment 2: Replenishing Social Networks

Experiment 1 provided evidence that when participants are given only group-type information (i.e., group label), they generate social networks differently. This suggests that people rely on prior knowledge—group-related network schemas—to guide their social network inferences. Since participants were told only about the number of social ties in the group, but not about their arrangement, they had to rely on their group-related network schema to make inferences. Stronger evidence for the existence of these schemas would be provided when participants were presented with partial social network data (i.e., initial social networks) and asked to infer the structure of a set number of additional potential relationships. Despite being given similar initial networks, participants would replenish them with different structures, due to being influenced by the group-related network schemas tied to different group types, and the replenished social networks in task groups would exhibit a lower average shortest path length and a higher degree centralization than those in social categories. Therefore, in this experiment, the participants were provided with an initial social network and asked to infer the arrangement of new potential friendships.

Methods

This experiment had almost the same design as that of Experiment 1 and thereby kept the same sample size as Experiment 1. A total of 42 participants were recruited, and two participants were excluded for failing to pass the attention check task. Therefore, data from a total of 40 participants (19 men and 21 women) with a mean age of 21.23 years

(SD = 2.11) were included in the final analysis. Each participant received approximately 20 RMB as compensation upon completing the experiment. All the participants were of Han ethnicity, which is the predominant ethnic group in China.

The procedure and design were nearly identical to those of Experiment 1, except that participants were provided with an initial social network and informed that they should infer three additional friendships between figures. This initial network included 12 existing pairs of friends (depicted by gray lines) that could not be altered while participants drew other new relationships. The initial social networks were carefully selected to ensure that they fell within the boundaries of the networks generated for the two group types in Experiment 1, making their classification into a specific group type more ambiguous. First, we calculated the average shortest path length and degree centralization for the 320 social networks generated by participants in Experiment 1 (e.g., 8 networks per participant). The median values for these networks were 2.222 for the average shortest path length and 0.178 for degree centralization, which were used as selection criteria for the initial networks. Second, we used the R package igraph (version 1.4.2) (Csardi & Nepusz, 2006) to randomly generate 1,000 social networks with 10 nodes (group members) and 12 edges (friendships). Finally, we identified 27 networks that met the selection criteria and randomly selected 16 networks as the initial networks. All participants were presented with the same 16 initial networks to ensure consistency. Each group label was assigned two initial networks, which were randomly matched for each participant, resulting in 16 trials. These trials were organized into two blocks, each presenting eight different group labels in a randomized sequence. In summary, all initial networks presented to participants had the same average shortest path length and degree centralization, differing only in their specific connection patterns.

After reviewing the descriptions of the labels at the top of the screen and the initial social network displayed on the left side of the screen, the participants were instructed to predict three potential friendships that could form between currently unconnected group members in the future. They were required to use lines to connect the figures representing the individuals in each inferred friendship.

Results

As illustrated in Figure 4, the average shortest path length of the replenished social networks in the task groups (M = 1.941, SE = 0.012) was significantly shorter than that in the social categories (M = 2.008, SE = 0.005; $t(39)$ = −4.37, $p < .001$, Cohen's d = −0.69, 95% CI [−1.01, −0.37]). In addition, the degree centralization of replenished social networks in task groups (M = 0.289, SE = 0.011) was significantly greater than that in social categories (M = 0.218, SE = 0.010; $t(39)$ = 4.00, $p < .001$, Cohen's d = 0.63, [0.31, 0.95]). These findings suggest that individuals are more inclined to strengthen connections and establish central persons within task groups than they are in social categories, even when starting with the same incomplete social network.

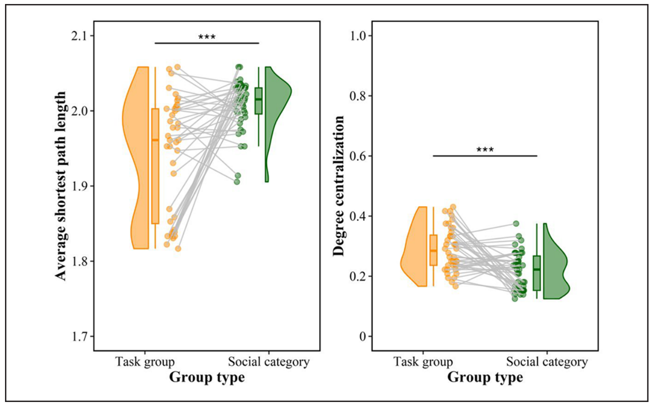

Figure 4. Average shortest path length and degree centralization for different group types in Experiment 2 with replenishing social networks.

Note. Left: the average shortest path length of social networks in task groups was significantly lower than that in social categories. Right: the degree centralization of social networks in task groups was significantly greater than that in social categories.

Experiment 3: Memorizing Social Networks

The first two experiments established that when no or partial network data are presented, group-related network schemas guide friendship inferences and representations. If these schemas play a role in social network representations, the way individuals encounter new network information that fits within their preexisting schemas could influence memory performance for social relationships. It has been suggested that cognitive schemas help us interpret and make sense of new information by connecting it to existing knowledge structures, and when new information aligns with existing cognitive schemas, it reduces the cognitive load, making it easier for individuals to encode and retrieve information and leading to better memory performance (Sweller, 1988, 2011). In this context, memory performance should also be enhanced because of more efficient encoding and easier access to relationships during recall. In support of this claim, the research by Brashears (2013) revealed that adults can recall a greater number of relationships with more detail when the network aligns with familiar group structures because cognitive schemas are activated. Therefore, Experiment 3 aimed to test whether participants' memory performance would improve when they were asked to memorize relationships from social networks that matched the group type, either task groups or social categories. If social network representation depends on group-related schemas, memory performance should improve when the memorized social network matches the group type, as the group type activates the aligned network schema.

Methods

Participants. We used the software G*Power 3.1 to calculate the planned sample size (Faul et al., 2007). Given that the main focused effect was whether the difference in memory performance for different network types was influenced by the group type in a within-subject design, we determined a minimum sample size of 34 participants on the basis of a medium effect size (d = 0.5), an alpha level of .05, and a power of 0.80. However, owing to the counterbalance of the experimental materials, which involved a total of eight versions (i.e., different combinations of network types and group types) and to ensure an equal number of participants for each version, we planned to recruit 40 valid participants. Notably, this sample size matched the participant count of our previous two completed studies, which employed different methods to investigate the same question as the present study did.

Finally, 43 participants were recruited. However, two participants were excluded for failing to pass the attention check task, and an additional participant was excluded because the accuracy was less than 20%. Therefore, data from a total of 40 participants were included in the analysis. The participants' ages ranged from 18 to 23 years (M = 19.95, SD = 1.93), with 23 males and 17 females. The participants received approximately 40 RMB as compensation upon completion of the experiment. All the participants were of Han ethnicity, which is the predominant ethnic group in China.

Experimental Stimuli. The experimental stimuli consisted of 2D simulated scenarios depicting social relationships. Each of the 10 figures (persons) was given a name for identification. Throughout each learning session, the depicted group (task group/social category) and its social relationships were presented. Two figures were shown alongside their relationship details. Concurrently, a diagram displaying 10 figures but omitting social connections within the group was shown in the upper left corner of the screen. This diagram emphasized the relative positions of the figures within the group to help participants understand the relationships. When two figures were presented for memorizing their relationship, the corresponding figures in the network diagram were highlighted in red, with their positions being consistent across different types of networks. This experiment was preregistered (https://doi.org/10.17605/OSF.IO/H3W8K; please note that the preregistration incorrectly described "a network diagram illustrating the social connections within the group" instead of the current description).

Considering the duration of the experiment, we selected the two most representative labels (i.e., those with the highest frequency) for each group type as stimuli for the current study. For task groups, "coworkers" and "students working on group assignments" were chosen, whereas for social categories, "teachers" and "civil servants" were selected. The entitativity ratings for these selected groups were marginally greater for social categories (M = 6.73, SE = 0.16) than for task groups (M = 6.32, SE = 0.18; $t(78)$ = 1.96, p = .053, Cohen's d = 0.22, 95% CI [0.00, 0.44]) in the pilot experiment.

In Experiment 1, participants were tasked with inferring the arrangement of relationships between group members when only the number of relationships and the group context were known. They were then asked to generate social networks from a top–down perspective based on different group types. Based on these findings, we collected networks with an average shortest path length less than the median and a more pronounced central tendency than the median for each group type separately. We subsequently selected the two most representative social networks from each group type, characterized by the average shortest path length and the highest degree centralization (Figure 5a and b). With respect to the four group labels and four social networks, we employed a pseudorandom method to generate eight predetermined combinations as experimental stimuli, which was counterbalanced among participants (please refer to Table S7).

The group members' names consist of two parts: "surname" and "given name." The "surname" is derived from publicly available data from the Ministry of Public Security of the People's Republic of China, specifically the top 40 surnames in the "100 surnames" list for the latest year (2020). These surnames include Wang (王), Li (李), Zhang (张), Liu (刘), Chen (陈), Yang (杨), Huang (黄), Zhao (赵), Wu (吴), Zhou (周), Xu (徐), Sun (孙), Ma (马), Zhu (朱), Hu (胡), Guo (郭), He (何), Lin (林), Luo (罗), Gao (高), Zheng (郑), Liang (梁), Xie (谢), Song (宋), Tang (唐), Xu (许), Han (韩), Deng (邓), Feng (冯), Cao (曹), Peng (彭), Zeng (曾), Xiao (肖), Tian (田), Dong (董), Pan (潘), Yuan (袁), Cai (蔡), Jiang (蒋), and Yu (余) (Ministry of Public Security, PRC, 2021).

To minimize the memory load and control for other irrelevant factors, the "given name" is uniformly replaced by "Mou (某)" to denote an unknown entity in Chinese. Consequently, a combination of the surname and "Mou" results in 40 names, for example, Li Mou (李某). Considering typicality and familiarity, the study balanced the names of group members across four groups, each comprising the top five surnames and the bottom five surnames (please refer to Table S8 for details).

Procedure and Design. The stimuli were displayed on a 15.6-inch LED monitor with a resolution of 1,920 × 1,080 pixels and a refresh rate of 120 Hz, positioned at a viewing distance of 60 cm from the participants. We utilized custom software developed in PsychoPy 3.0 to present the stimuli (Peirce et al., 2019).

The participants were informed that they would be required to learn about the relationships among 10 persons

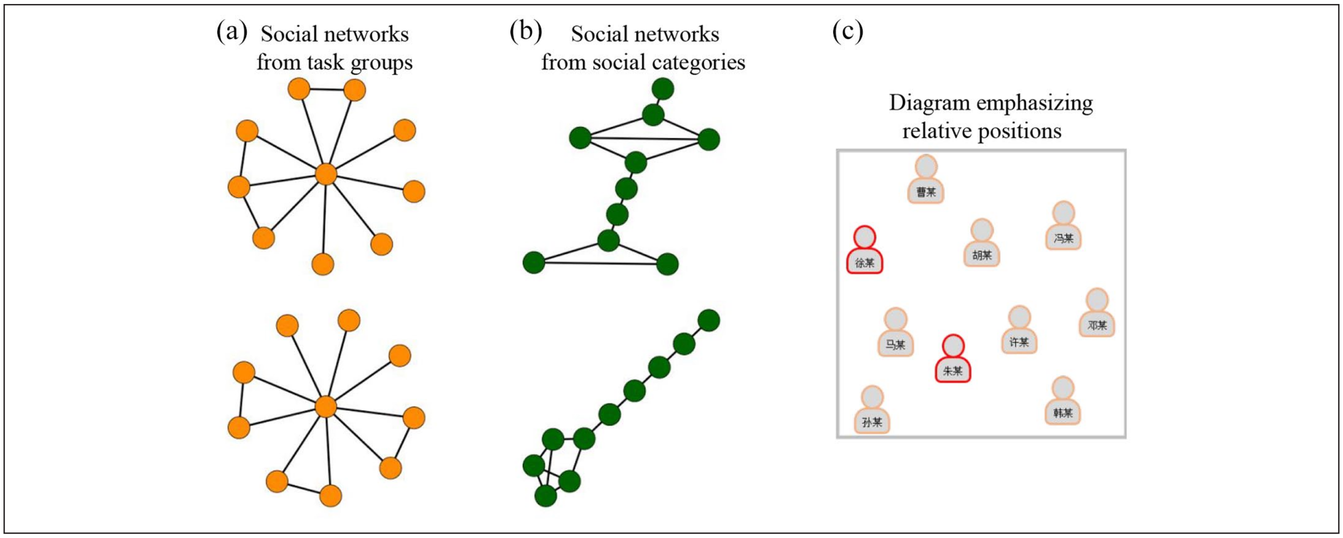

Figure 5. Social networks used in Experiment 3.
Note. Based on the social networks generated in Experiment 1, we selected two representative networks (a) and (b) from each group type. It is important to note that the layout of the social networks uses the Kamada-Kawai layout algorithm from the igraph library in R, which differs from how participants originally generated them in Experiment 1; this layout merely visualizes the connections between individuals in the network. (c) Presents the positions of 10 figures consistently across different network types.

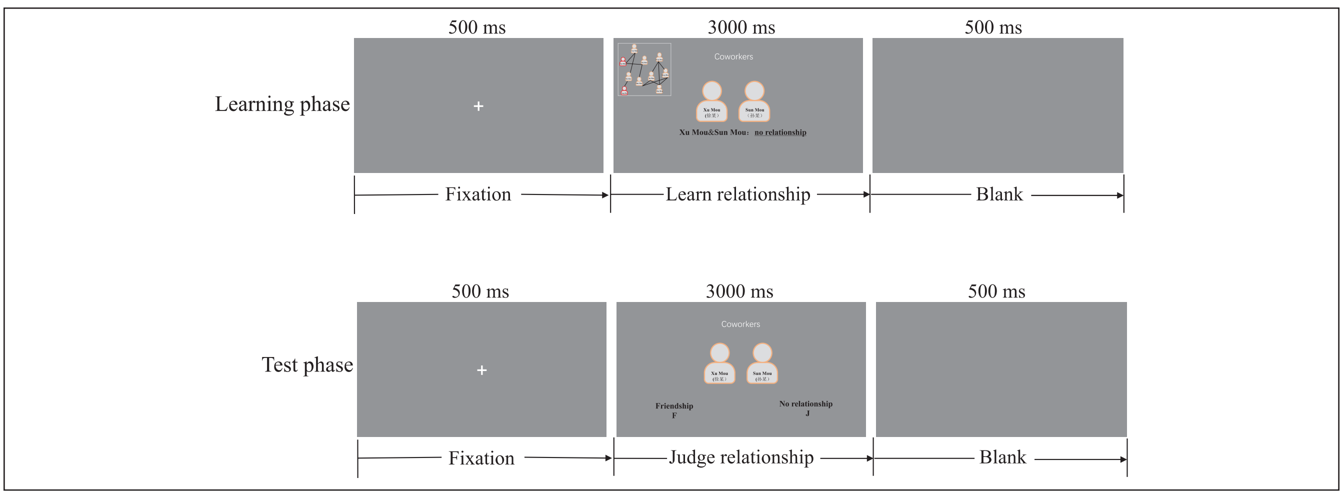

Figure 6. An example of a trial sequence for the learning phase and test phase.
Note. In the learning phase, participants were presented with two figures and information about their relationship (e.g., "XX and XX have a friendship/no relationship"), along with a label at the top of the screen indicating the group membership of the depicted individuals. The participants were instructed to memorize these relationships as accurately as possible. During the test phase, they were required to quickly judge the relationship between the two presented individuals on the basis of their memory from the learning phase.

within a group and memorize them as accurately as possible for subsequent testing. The experiment consisted of two phases within each block: the learning phase and the test phase (Figure 6). Considering which group type would generate the social network and the corresponding label describing the group type, the experimental design employed a within-subject design with two factors: network type (task group vs. social category) and group type (task group vs. social category). Here, the network type indicates the type of group generating the social network during the learning phase, whereas the group type refers to the type of group described by the label. Each condition consisted of one block, for a total of four blocks. To control for sequence effects, the order of these blocks was randomized for each participant.

In each block, the learning phase comprised 45 pairs designed to present all the relationships among the 10 persons in the group. The participants completed two rounds of learning with different randomized orders, resulting in a total of 90 trials. Following the learning phase, the participants took a 5-min break before proceeding to the test phase. During the test phase, participants were tested on whether a friendship existed for each of the possible 45 pairs of persons. In each block, the social network describing relationships varied, with only 10 pairs of persons having friendships, whereas the remaining pairs had no relationship. However, the participants were not informed of this arrangement. After completing all the blocks, similar to the procedure in Experiment 1, the participants were required to perform an attention check task to verify whether they had paid attention to the group labels presented at the top of the screen. To familiarize participants with the experimental procedure, a practice session similar to the formal experiment was designed. This practice experiment also comprised a learning phase and a test phase. The participants were instructed to memorize the relationships among five group members from the associated group (i.e., individuals traveling in the same tour group). However, the results of the practice session were not recorded.

In the learning phase, each trial started with the presentation of a fixation cross, which was displayed for 500 ms. Following this, two stick figures representing two persons were displayed at the center of the screen with slight separation, each labeled with a name, which was displayed for 3,000 ms. Below the figures, their relationship (e.g., "XX and XX have a friendship/no relationship") was shown. At the top of the screen, a label indicates the group membership of the depicted persons. Four different group labels were used, representing two types of groups: coworkers and students working on group assignments together (task groups) and teachers and civil servants (social categories). The same group label was consistently applied within each block, with each block featuring distinct labels, resulting in four blocks in total. To emphasize which two persons were friends within the group and facilitate participants' learning of the relationships, a network diagram illustrating the relationships within the group was displayed in the upper left corner of the screen, with the two persons whose relationship was to be learned highlighted (Figure 5c; the positions of 10 figures remained consistent across different network types). A blank screen was subsequently presented for 500 ms before the start of the next learning trial. All dyadic relationships were presented randomly, and participants were given the option to either take a short break or continue learning after every 15 trials.

The test phase was similar to the learning phase, with the exceptions described below. The network diagram was removed, and the text describing the relationship between the two persons portrayed was removed but presented with "F: friendship; J: relationship." The participants were required to quickly judge the relationship between the two presented persons on the basis of their memory from the learning phase. They pressed the "F" key if there was a friendship between the two persons or the "J" key if there was no relationship, with a response time limit of 3,000 ms and no feedback provided.

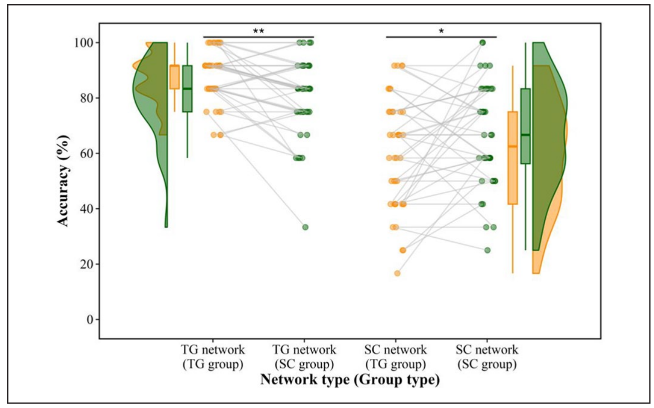

Figure 7. Memory accuracy as a function of network type and group type in Experiment 3.

Note. Memory accuracy is greater when the memorized network structure aligns with the group type that originally generated it than in instances where they are not aligned.

TG = task group; SC = social category.

Data Analysis. The memory accuracy of participants in recalling friendships during the test phase was computed. Specifically, for each condition, we calculated the ratio of successfully recalled pairs (K) to the total number of friendship pairs presented (N) during the learning phase, that is, K/N. In addition, response times for each condition were recorded for exploratory analysis.

Results

Figure 7 shows the memory accuracy for friendships. The accuracy data were summed into a 2 (network type: task group vs. social category) × 2 (group type: task group vs. social category) repeated-measures ANOVA. The results revealed that the main effect of network type was significant ($F(1, 39) = 72.38$, $p < .001$, $\eta_p^2 = 0.65$, 95% CI [0.50, 0.75]), indicating that the accuracy of social relationship memorization for the task group ($M = 83.9\%$, $SE = 1.6\%$) was greater than that for the social category ($M = 63.3\%$, $SE = 2.6\%$). The main effect of group type was not significant ($F(1, 39) < 0.01$, $p = .959$, $\eta_p^2 < 0.01$, [0.00, 0.00]). However, the interaction between them reached significance ($F(1, 39) = 14.18$, $p < .001$, $\eta_p^2 = 0.27$, [0.09, 0.44]).

To explore this interaction, we performed simple effect tests for each group type. These tests revealed that participants had better memory accuracy when the learned networks originally generated from task groups were described as being from the task group type ($M = 87.3\%$, $SE = 1.5\%$) than from the social category type ($M = 80.4\%$, $SE = 2.2\%$; $t(39) = 3.40$, $p = .002$, Cohen's $d = 0.36$, 95% CI [0.15, 0.58]). Conversely, participants had lower memory accuracy when the learned networks originally generated from social categories were described as being from the task group type ($M = 59.8\%$, $SE = 3.2\%$) than when they were described as being from the social category type ($M = 66.9\%$,

SE = 3.0%; $t(39) = -2.13$, $p = .040$, Cohen's $d = -0.38$, [−0.73, −0.02]). The results indicate that, regardless of whether the social network is generated from task groups or social categories, memory accuracy is greater when the memorized network structure aligns with the group type that originally generated it than when they are not aligned (short for the matching effect).

Explorative Analysis. We conducted an ANOVA for response time data similar to that conducted for accuracy. The results revealed that only the main effect of the network type was significant ($F(1, 39) = 106.71$, $p < .001$, $\eta_p^2 = 0.73$, 95% CI [0.61, 0.81]), indicating that recalling the relationships from the social category (M = 1,674 ms, SE = 45) took more time than recalling those from the task group (M = 1,212 ms, SE = 34). Neither the main effect of group type ($F(1, 39) = 0.20$, $p = .655$, $\eta_p^2 < 0.01$, [0.00, 0.10]) nor the interaction effect ($F(1, 39) = 0.66$, $p = .422$, $\eta_p^2 = 0.02$, [0.00, 0.13]) was significant.

We explored whether the above finding was specific to memorizing friendships by computing the accuracy of memorizing no relationships (see Table S6), which is the ratio of successfully recalled pairs with no relationship to the total number of pairs without a relationship presented during the learning phase. Only the main effect of network type was found to be significant, showing that the accuracy of memorizing no social relationship for the task group (M = 83.9%, SE = 1.6%) was greater than that for the social category (M = 63.3%, SE = 2.6%). Neither the main effect of group type ($F(1, 39) = 0.20$, $p = .655$, $\eta_p^2 < 0.01$, 95% CI [0.00, 0.10]) nor the interaction effect ($F(1, 39) = 0.66$, $p = .422$, $\eta_p^2 = 0.02$, [0.00, 0.13]) was significant. Hence, the matching effect is specific to memorizing social relationships.

Discussion

Our social lives heavily depend on the efficient representation of social networks, a process that poses significant challenges but can be facilitated by cognitive schemas. In this study, we conducted three experiments to investigate whether social network representation relies on schemas associated with group typology. The results indicated that, even without information about the arrangement of relationships—only their number—the participants generated social networks for task groups that were more closely connected and more likely to feature centralized structures than those for social categories (Experiment 1). Furthermore, the labels associated with different group types in Experiment 2 biased the participants' inferences about the future structure of social relationships within social networks with available network data, leading to network structures similar to those observed in Experiment 1. When the participants learned about the social networks corresponding to different group types in Experiment 3, accuracy was greater when the learned network matched the expected group type that activated the aligned network schema, regardless of whether the network was from a task group or a social category. These findings suggest that individuals represent social networks on the basis of group-related schemas, wherein task groups are believed to have closer and more centralized connections than social categories.

Some may argue that our findings simply reflect the perception that task groups exhibit greater groupness (i.e., entitativity) than social categories do, which might lead participants to assume closer connections among group members rather than truly reflecting how the social network should be structured. However, this interpretation does not hold, as our results showed that perceived entitativity was actually greater for social categories than for task groups (see the results reported in the Methods sections of Experiments 1 and 3, as well as the procedure described in Pilot Experiment B). In addition, the same number of friendship pairs had to be represented in both group types. In Experiment 3, the participants engaged in a memory task without needing to draw social networks. In this task, when the actual network learned matched the group type—meaning the group-related schema was aligned with the learned network—memory accuracy was significantly enhanced. This provides more direct evidence that group-related schemas play a critical role in representing social networks beyond simply reflecting perceived entitativity.

It is possible that social categories (e.g., doctors and teachers) may not inherently imply friendships, potentially leading participants to make more arbitrary inferences about social ties. However, on the basis of our experimental design and further analysis of the results, we believe that comparing task groups and social categories provides valuable insight into how people's schemas shape their representations of social networks. First, social categories often evoke a sense of belonging and solidarity, which can lay the groundwork for forming friendships. In our study, the participants were informed that 12 pairs of friends existed. Second, we carefully selected labels within both task groups and social categories that participants likely associated with implicit social structures, and we revealed systematic differences between the inferred network structures of these group types. To strengthen this analysis, we separated the results by eight separate labels in the Supplemental Material. This additional analysis revealed that network metric differences were mostly between group types (see Figures S3, S4, and S5). Furthermore, by providing partial network data in Experiment 2, which reduced individual variation, we demonstrated that structural metrics of social networks differed primarily between group types. Mixed-effects models, with the group label as a random effect, further supported the main findings. Finally, to investigate whether participants randomly impute social networks for social categories, we generated random networks with 10 nodes and 12 ties. Our results indicated that participants did not randomly generate social ties, supporting the existence of group-related schemas (see the fourth section of the Supplemental Material). Moreover, if participants did not expect relationships within social categories, memory performance for "no relation" should have been enhanced when the networks were described as originating from social categories compared with task groups. However, this finding was inconsistent with our findings, where no significant differences were observed. Importantly, if participants had no expectations about the structure of social networks in social categories, the alignment of the learned networks with their schemas should not have led to any memory enhancement. This is not the case in our study, further supporting the existence of schemas that influence network representations.

The current work expands on existing research by integrating group typology into cognitive schemas. While previous studies have focused primarily on schemas related to local connections, such as triadic closure (Brashears, 2013; Flynn et al., 2010), and some have examined global structures, such as kinship networks or small-world networks (Brashears, 2013; Kilduff et al., 2008; Schwyck, 2023), they have not fully explored how cognitive network schemas apply to different group contexts. As an exploratory addition, a further experiment supported the idea that people have group-related schemas for how relationships are structured in task groups versus intimacy groups (see Experiment S1 of the Supplemental Material). This distinction highlights the different ways individuals organize and represent the relationships within these different types of groups. Previous research has suggested that people naturally use group typology to organize information about groups, as evidenced by the tendency to make more errors within the same group type than between different group types (Sherman et al., 2002). Our findings extend this understanding by demonstrating that group typology also includes relational knowledge about how group members are structured. This knowledge has adaptive value, where the representation of social networks is linked to the neocortex ratio of the brain, which influences the capacity to maintain large social networks (Dunbar, 2003; Falk & Bassett, 2017; Noonan et al., 2018; Schmälzle et al., 2017; Stiller & Dunbar, 2007). The schemas of social networks are cognitive structures that make up the network knowledge base and serve as compression heuristics, facilitating the efficient storage of large amounts of social relationship information within the brain, which has a limited capacity. This extends the concept of triadic closure and kinship-based network schemas proposed by Brashears (2013) to group types, highlighting their role in shaping social network representations. Importantly, however, the schema for social networks may be limited to the presence of social relationships, at least for the group-related schemas identified in this study. Specifically, Experiment 3 revealed a matching effect for recalling only pairs of individuals with established relationships, which is consistent with findings from Schwyck (2023). Future research should further investigate the specific contents of group-related schemas.

How does the group-related schema form? It is likely learned through statistical regularities observed in social networks associated with different group types, meaning that its acquisition may occur through experiential learning. Previous studies have shown that task groups, which are formed to achieve a common goal, and social categories, which are based on shared identities, tend to exhibit different structural patterns (Lickel et al., 2006; Shea & Fitzsimons, 2016). Over time, these regularities in the daily data may become encoded in our brains. In support of this idea, our simulation results from ChatGPT (Open AI) , which learns from statistical patterns in training data and align with the human-generated data (see the Supplemental Material). This suggests that group-related schemas can be acquired through statistical learning from accumulated social experiences. However, even in the absence of direct experience with specific network structures, individuals may still have an instinctive understanding of social groups. From an adaptive perspective, close and centralized networks are more effective at achieving collective goals, as observed in task groups, whereas more decentralized networks may better fulfill attachment needs, which are characteristic of social categories (Hughes et al., 2024; Tröster et al., 2014). This suggests that group-related schemas may have evolved to optimize different social functions. Possibly, while task groups may activate more context-specific schemas due to their goal-oriented nature, participants in the social category condition may instead draw on more generic or default schemas when explicit information (e.g., number of friendships) is lacking. In such cases, participants likely would not assume connections among members unless told how many ties to expect, reflecting the weaker relational expectations within social categories. This highlights the importance of investigating how both experiential learning and intuitive social understanding contribute to the development and application of cognitive schemas in network representation.

The findings of Experiment 3 have important implications for quantitatively assessing the capacity to represent social networks. Notably, memory performance was superior for networks derived from task groups compared with those derived from social categories. The networks from task groups, characterized by closer and more centralized connections, presented a shorter average shortest path length and a greater degree of centralization than those from social categories. This suggests that social networks with these structural properties might be better memorized and more efficiently stored. Future research should explore this hypothesis to better understand the relationship between network structure and memory performance.

Several limitations need to be considered. First, this study focused primarily on friendships, which do not capture the full range of social relationships that people encounter in their daily lives. Future studies should explore how these diverse types of social relationships, such as those involving advice seeking and dominance, are represented and whether similar cognitive schemas apply. Another limitation concerns the role of individual differences, such as personal centralization within one's own social network, or personality traits such as extroversion or openness to experience. In addition, cultural background shapes how friend relationships are understood. For example, in some cultures, such as Russia, friendship is limited to a small number of deeply meaningful relationships. In contrast, in other cultures, such as China, people with more superficial interactions might still be considered friends. These factors could influence how people form and apply group-related schemas, which should be more thoroughly examined in future research. The number of nodes in a social network also presents a potential limitation. The network size was not systematically varied in the current study, which could impact the generalizability of the findings. Larger networks may impose greater cognitive demands, potentially altering the effectiveness of schema-based representation. Understanding how the number of nodes influences social network representation is essential for a more comprehensive understanding of social cognition.

In conclusion, this study highlights the significant role of cognitive network schemas related to group typology in shaping how individuals represent social networks. Specifically, this research shows that social networks associated with task groups tend to be more closely connected and centralized than those related to social categories. This extends our understanding of group-level schemas by demonstrating that they encompass relational knowledge about network structures, thereby facilitating the efficient processing of social information.

Author Contributions

Yi Zhang: Conceptualization; Investigation; Methodology; Visualization; Writing—original draft; Writing—review & editing. **Danfeng Ai:** Conceptualization; Investigation; Methodology; Visualization; Writing—original draft; Writing—review & editing. **Jade Li Wang:** Conceptualization; Investigation; Visualization; Writing—review & editing. **Lei Ji:** Investigation; Writing—original draft; Writing—review and editing. **Ying Zhou:** Investigation; Writing—original draft; Writing—review and editing. **Jipeng Duan:** Investigation; Methodology; Writing—original draft; Writing—review and editing. **Jun Yin:** Conceptualization; Methodology; Supervision; Visualization; Writing—original draft; Writing—review and editing.

Declaration of Conflicting Interests

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Data Availability Statement

All data and analysis codes have been made publicly available on the Open Science Framework (OSF) and can be accessed at https://osf.io/2cwmu. Experiments 1 and 2 were not preregistered. However, Experiment 3 was preregistered and can be accessed at https://doi.org/10.17605/OSF.IO/H3W8K.

Ethics

This research, titled "Social Network Representation," received approval from the local ethics board.

Artificial Intelligence

During the writing of this paper, we used ChatGPT 3.5 to enhance readability and improve the clarity of language.

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Supplemental Material

Supplemental material is available online with this article.

Note

1. It is interesting to study social network representations for intimacy groups. While intimacy groups mainly refer to families, couples, and friends, and these relationships are relatively stable, even for a group of friends, the members in this group must have friendships with other individuals, leaving less room for flexibly manipulating friendship networks. However, for social categories, people often feel a sense of belonging and solidarity within their social categories, which can serve as a foundation for friendships.

References

Bao H. (2025). *bruceR: Broadly Useful Convenient and Efficient R Functions*. R package version 2024.6. https://psychbruce.github.io/bruceR/

Basyouni, R., & Parkinson, C. (2022). Mapping the social landscape: Tracking patterns of interpersonal relationships. *Trends in Cognitive Science*, *26*(3), 204–221. https://doi.org/10.1016/j.tics.2021.12.006

Bayer, J. B., Lewis, N. A., Jr, & Stahl, J. L. (2020). Who comes to mind? Dynamic construction of social networks. *Current Directions in Psychological Science*, *29*(3), 279–285. https://doi.org/10.1177/0963721420915866

Bernstein, E. S., Shore, J., & Jang, A. J. (2022). Network centralization and collective adaptability to a shifting environment. *Organization Science*, *34*(6), 2064–2096. https://doi.org/10.1287/orsc.2022.1584

Boguñá, M., Bonamassa, I., De Domenico, M., Havlin, S., Krioukov, D. V., & Serrano, M. Á. (2020). Network geometry. *Nature Reviews Physics*, *3*, 114–135. https://doi.org/10.1038/s42254-020-00264-4

Brands, R. A. (2013). Cognitive social structures in social network research: A review. *Journal of Organizational Behavior*, *34*(Suppl 1), S82–S103. https://doi.org/10.1002/job.1890

Brashears, M. E. (2013). Humans use compression Heuristics to improve the recall of social networks. *Scientific Reports*, *3*, 1513. https://doi.org/10.1038/srep01513

Brass, D. (2022). New developments in social network analysis. *Annual Review of Organizational Psychology and Organizational Behavior*, *9*(1), 225–246. https://doi.org/10.1146/annurev-orgpsych-012420-090628

Crockett, W. H. (1982). Balance, agreement, and positivity in the cognition of small social structures. *Advances in Experimental Social Psychology*, *15*, 1–57. https://doi.org/10.1016/S0065-2601(08)60294-4

Csardi, G., & Nepusz, T. (2006). "The igraph software package for complex network research." *InterJournal, Complex Systems*, *1695*. https://igraph.org

De Dreu, C. K. W., Gross, J., & Romano, A. (2024). Group formation and the evolution of human social organization. *Perspectives on Psychological Science*, *19*(2), 320–334. https://doi.org/10.1177/17456916231179156

Dunbar, R. I. M. (2003). The social brain: Mind, language, and society in evolutionary perspective. *Annual Review of Anthropology*, *32*, 163–181. https://doi.org/10.1146/annurev.anthro.32.061002.093158

Falk, E. B., & Bassett, D. S. (2017). Brain and social networks: Fundamental building blocks of human experience. *Trends in Cognitive Science*, *21*(9), 674–690. https://doi.org/10.1016/j.tics.2017.06.009

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*, 175–191.

Flynn, F. J., Reagans, R. E., & Guillory, L. (2010). Do you two know each other? Transitivity, homophily, and the need for (network) closure. *Journal of Personality and Social Psychology*, *99*(5), 855–869. https://doi.org/10.1037/a0020961

Freeman, L. C. (1979). Centrality in social networks conceptual clarification. *Social Networks*, *1*(3), 215–239. https://doi.org/10.1016/0378-8733(78)90021-7

Halford, G. S., Wilson, W. H., & Phillips, S. (2010). Relational knowledge: The foundation of higher cognition. *Trends in Cognitive Sciences*, *14*(11), 497–505. https://doi.org/10.1016/j.tics.2010.08.005

Hughes, E. A., Ellis, S., & Smith, J. R. (2024). Connecting groups and behaviours: A network analysis of identity-infused behaviours. *The British Journal of Social Psychology*, *63*(1), 205–233. https://doi.org/10.1111/bjso.12674

Janicik, G. A., & Larrick, R. P. (2005). Social network schemas and the learning of incomplete networks. *Journal of Personality and Social Psychology*, *88*(2), 348–364. https://doi.org/10.1037/0022–3514.88.2.348

Johnson, A. L., Crawford, M. T., Sherman, S. J., Rutchick, A. M., Hamilton, D. L., Ferreira, M. B., & Petrocelli, J. V. (2006). A functional perspective on group memberships: Differential need fulfillment in a group typology. *Journal of Experimental Social Psychology*, *42*(6), 707–719. https://doi.org/10.1016/j.jesp.2005.08.002

Jolly, E., & Chang, L. J. (2021). Gossip drives vicarious learning and facilitates social connection. *Current Biology*, *31*(12), 2539–2549. https://doi.org/10.1016/j.cub.2021.03.090

Kazak, A. E. (2018). Editorial: Journal article reporting standards. *American Psychologist*, *73*(1), 1–2. https://doi.org/10.1037/amp0000263

Kilduff, M., Crossland, C., Tsai, W., & Krackhardt, D. (2008). Organizational network perceptions versus reality: A small world after all? *Organizational Behavior and Human Decision Processes*, *107*(1), 15–28. https://doi.org/10.1016/j.obhdp.2007.12.003

Krackhardt, D., & Kilduff, M. (1999). Whether close or far: Social distance effects on perceived balance in friendship networks. *Journal of Personality and Social Psychology*, *76*, 770–782. https://doi.org/10.1037/0022-3514.76.5.770

Lickel, B., Hamilton, D. L., & Sherman, S. J. (2001). Elements of a lay theory of groups: Types of groups, relational styles, and the perception of group entitativity. *Personality and Social Psychology Review*, *5*, 129–140. https://doi.org/10.1207/S15327957PSPR0502_4

Lickel, B., Hamilton, D. L., Wieczorkowska, G., Lewis, A., Sherman, S. J., & Uhles, A. N. (2000). Varieties of groups and the perception of group entitativity. *Journal of Personality and Social Psychology*, *78*(2), 223–246. https://doi.org/10.1037//0022-3514.78.2.223

Lickel, B., Rutchick, A. M., Hamilton, D. L., & Sherman, S. J. (2006). Intuitive theories of group types and relational principles. *Journal of Experimental Social Psychology*, *42*(1), 28–39. https://doi.org/10.1016/j.jesp.2005.01.007

Ministry of Public Security, PRC. (2021). *The 2020 National Name Report*, 1. https://www.gov.cn/xinwen/2021-02/08/content_5585906.htm

Newman, M. E. J. (2010). *Networks: An introduction*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199206650.001.0001

Noonan, M. P., Mars, R. B., Sallet, J., Dunbar, R. I. M., & Fellows, L. K. (2018). The structural and functional brain networks that support human social networks. *Behavioural Brain Research*, *355*, 12–23. https://doi.org/10.1016/j.bbr.2018.02.019

Papeo, L., Goupil, N., & Soto–Faraco, S. (2019). Visual search for people among people. *Psychological Science*, *30*(10), 1483–1496. https://doi.org/10.1177/0956797619867295

Peer, M., Hayman, M., Tamir, B., & Arzy, S. (2019). Brain coding of social network structure. *The Journal of Neuroscience*, *41*, 4897–4909. https://doi.org/10.1523/JNEUROSCI.2641-20.2021

Peirce, J., Gray, J. R., Simpson, S., MacAskill, M., Höchenberger, R., Sogo, H., Kastman, E., & Lindelov, J. K. (2019). PsychoPy2: Experiments in behavior made easy. *Behavior Research Methods*, *51*(1), 195–203.

R Core Team. (2023). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. https://R-project.org/

Schmälzle, R., Brook O'Donnell, M., Garcia, J. O., Cascio, C. N., Bayer, J., Bassett, D. S., Vettel, J. M., & Falk, E. B. (2017). Brain connectivity dynamics during social interaction reflect social network structure. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(20), 5153–5158. https://doi.org/10.1073/pnas.1616130114

Schwyck, M. E. (2023). *Tracking relationships: Uncovering how people acquire, represent, use, and predict social network information[M]*. University of California.

Scott, J., & Carrington, P. J. (2011). *The SAGE handbook of social network analysis*. Sage Publications Ltd. https://doi.org/10.4135/9781446294413

Shea, C. T., & Fitzsimons, G. M. (2016). Personal goal pursuit as an antecedent to social network structure. *Organizational*

Behavior and Human Decision Processes, *137*, 45–57. https://doi.org/10.1016/j.obhdp.2016.07.002

Sherman, S. J., Castelli, L., & Hamilton, D. L. (2002). The spontaneous use of a group typology as an organizing principle in memory. *Journal of Personality and Social Psychology*, *82*(3), 328–342. https://doi.org/10.1037/0022-3514.82.3.328

Smith, E. B., Brands, R. A., Brashears, M. E., & Kleinbaum, A. M. (2020). Social networks and cognition. *Annual Review of Sociology*, *46*, 159–174. https://doi.org/10.1146/annurev-soc-121919-054736

Son, J. Y., Bhandari, A., & FeldmanHall, O. (2021). Cognitive maps of social features enable flexible inference in social networks. *Proceedings of the National Academy of Sciences of the United States of America*, *118*(39), e2021699118. https://doi.org/10.1073/pnas.2021699118

Son, J. Y., Bhandari, A., & FeldmanHall, O. (2023). Abstract cognitive maps of social network structure aid adaptive inference. *Proceedings of the National Academy of Sciences*, *120*(47), e2310801120. https://doi.org/10.1073/pnas.2310801120

Son, J. Y., Vives, M. L., Bhandari, A., & FeldmanHall, O. (2024). Replay shapes abstract cognitive maps for efficient social navigation. *Nature Human Behaviour*, *8*(11), 2156–2167. https://doi.org/10.1038/s41562-024-01990-w

Stiller, J., & Dunbar, R. I. M. (2007). Perspective-taking and memory capacity predict social network size. *Social Networks*, *29*(1), 93–104. https://doi.org/10.1016/j.socnet.2006.04.001

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science*, *12*(2), 257–285. https://doi.org/10.1207/s15516709cog1202_4

Sweller, J. (2011). Chapter two—Cognitive load theory. In J. P. Mestre & B. H. Ross (Eds.), *Psychology of Learning and Motivation* (*Vol. 55*, pp. 37–76). Academic Press. https://doi.org/10.1016/B978-0-12-387691-1.00002-8

Tatone, D., & Csibra, G. (2024). The representation of giving actions: Event construction in the service of monitoring social relationships. *Current Directions in Psychological Science*, *33*(3), 159–165. https://doi.org/10.1177/09637214241242460

Tröster, C., Mehra, A., & van Knippenberg, D. (2014). Structuring for team success: The interactive effects of network structure and cultural diversity on team potency and performance. *Organizational Behavior and Human Decision Processes*, *124*(2), 245–255. https://doi.org/https://doi.org/10.1016/j.obhdp.2014.04.003

Vestner, T., Tipper, S. P., Hartley, T., Over, H., & Rueschemeyer, S. A. (2019). Bound together: Social binding leads to faster processing, spatial distortion, and enhanced memory of interacting partners. *Journal of Experimental Psychology: General*, *148*(7), 1251–1268. https://doi.org/10.1037/xge0000545

Weaverdyck, M. E., & Parkinson, C. (2018). The neural representation of social networks. *Current Opinion in Psychology*, *24*, 58–66. https://doi.org/10.1016/j.copsyc.2018.05.009

Wickham, H. (2016). *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York. https://ggplot2.tidyverse.org/

Yin, J., Csibra, G., & Tatone, D. (2022). Structural asymmetries in the representation of giving and taking events. *Cognition*, *229*, 105248. https://doi.org/10.1016/j.cognition.2022.105248