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Group-Related Network Schema Guides the Learning of Social Networks

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Navigating complex social environments requires understanding how individuals are connected within social networks. People are highly efficient at integrating dyadic relationships into larger network structures. However, social networks are embedded within different types of groups (e.g., task groups vs. social categories), raising the question of how group typology shapes the learning and representation of social networks. Across four experiments, we demonstrate that group-related network schemas—specifically, expectations that task groups are more interconnected and centralized than social categories—systematically guide social network learning and representation. Participants exhibited prior expectations about the relational structure of different group types, and memory for social relationships was enhanced when the learned network structure aligned with these schematic expectations, producing a matching effect that was correlated with schema strength (Experiment 1). This effect was causally driven by schema strength: Weakening group-related schemas through explicit descriptions attenuated the matching effect (Experiment 2). Critically, the effect was domain specific: When social relationships were replaced with nonsocial connections (airport–flight networks), the matching effect disappeared despite comparable structural properties and task demands (Experiment 3). Computational modeling using the Successor Representation framework further revealed that schema–structure misalignment reduced multistep abstraction, reflected in lower successor discount parameters (γ), yielding less integrated global representations of social networks (Experiment 4). Together, these findings show that social network learning is guided by top-down group-related schemas. It advances our understanding of social network cognition by highlighting the importance of schema-driven abstraction and by bridging local learning mechanisms with global representational structure.

Public Significance Statement

This research shows that people do not learn social networks as simple lists of who is connected to whom. Instead, they rely on their expectations about different kinds of groups—such as work teams versus social categories—to understand how people are connected. When a social network fits these expectations, people remember relationships more accurately and build clearer mental pictures of the group. When it does not, learning becomes harder. Importantly, this effect becomes stronger when people hold stronger expectations about the group and does not occur for nonsocial networks, showing that social meaning plays a key role in how we learn about social connections. Computer modeling further shows that when expectations and network structure do not match, people form less organized mental representations of social networks. Together, these findings help explain how people make sense of complex social worlds.

Keywords: cognitive schema, group typology, task group, social category, social network

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Our social world is remarkably complex, with individuals embedded in intricate social networks. Effective social navigation requires the capacity to recognize and remember these structures, as this knowledge allows people to predict behavior, reciprocate favors, and mitigate conflict (Bayer et al., 2020; Xia et al., 2025). For example, when entering a new environment like a school, one must accurately map the social ties among peers to facilitate appropriate interactions. Despite being a critical human necessity, the scale of these networks presents a daunting computational challenge (Dunbar, 2014; Dunbar & Shultz, 2007). A typical social circle of 150 people—known as Dunbar's number—involves 11,175 potential dyadic relationships. Understanding how the human mind learns and remembers such vast amounts of social information is therefore essential to unraveling the mechanisms of social navigation.

While the dyadic relationship is the foundational unit of social life (McMahon & Isik, 2023; Yin et al., 2022), relying solely on dyadic representations is cognitively inefficient. As the number of tracked individuals grows, the computational demand of storing every unique pair increases exponentially, creating a significant cognitive load (Basyouni & Parkinson, 2022; Janicik & Larrick, 2005). Crucially, isolated dyadic knowledge fails to support inferences regarding the broader community structure, such as an individual's relative influence or brokerage potential. To address these limitations, recent research advocates for a social network representation framework (Basyouni & Parkinson, 2022; Son et al., 2023). This approach suggests that individuals move beyond merely identifying "who is friends with whom" to understanding the "global structure" of their community. Within this framework, dyadic ties are integrated into larger mental maps where individuals are represented as nodes and their interpersonal relationships (e.g., friendships) as edges. Based on such representations, individuals can form accurate, abstract understandings of their network's global structure (e.g., community and clique membership), which in turn supports effective navigation of the social landscape and facilitates upward movement within the social structure (Aslarus et al., 2025).

However, representing these networks presents a staggering cognitive challenge. As group size increases, constrained by finite capacity, we are often unable to learn every specific tie with perfect fidelity and frequently lack detailed knowledge about individual connections (Stiller & Dunbar, 2007). To overcome these limitations, researchers propose that we represent social networks as structured "cognitive maps" rather than mere lists of facts (Brashears, 2013; Flynn et al., 2010; Janicik & Larrick, 2005). To manage vast social connections, the brain utilizes cognitive network schemas as "compression heuristics"—mental shortcuts that function like "lossy compression" algorithms (Brands, 2013; Schwyck et al., 2025). Much like a low-resolution image preserves general shapes while discarding fine details, these schemas allow individuals to reconstruct the "gist" of a social structure. For instance, a balance schema might prompt us to "fill in the blanks" using rules like transitivity (e.g., if A knows B, and B knows C, then A likely knows C; Crockett, 1982; Krackhardt & Kilduff, 1999). By leveraging prior knowledge to organize relational data, social network schemas provide a cognitive scaffolding that helps individuals navigate unfamiliar or incomplete networks (Janicik & Larrick, 2005). Ultimately, these structural templates transform the computationally exhaustive task of remembering thousands of individual ties into a streamlined and manageable inferential process.

Historically, research on network schemas has centered on local rules, such as transitivity ("a friend's friend is a friend") or triadic closure (Basyouni & Parkinson, 2022; Flynn et al., 2010; Janicik & Larrick, 2005; Son et al., 2023). While powerful, these local schemas are insufficient for capturing the global topology of entire groups. Social networks do more than represent interpersonal ties; they provide the structural foundation for social groups (Zhang et al., 2025). However, the influence of global group-level schemas on network learning remains underexplored. Recent work highlights that cultural schemas (e.g., kinship systems) induce clear expectations about relationship patterns, significantly enhancing memory when a network aligns with these schemas (Brashears, 2013). Furthermore, individuals in brokerage positions—those who connect disparate social clusters—excel at learning networks that mirror typical real-world structures (Schwyck et al., 2025). This suggests that humans form global community-level schemas to facilitate learning. Nevertheless, existing research rarely addresses the group's typology itself. Social networks do not exist in a vacuum; they are inherently embedded within specific group contexts—such as task groups or social categories—each possessing distinct structural signatures (Lickel et al., 2001, 2006). Therefore, it is essential to investigate the role of group-related network schemas in shaping how we learn and represent social networks.

Previous accounts of schemas at the group level suggest that group members are represented as densely interconnected through a community schema, which can lead people to heuristically infer relationships that do not actually exist among group members. (Freeman & Webster, 1994; Son et al., 2023). Nevertheless, social groups are not homogeneous and have been proposed to fall into four distinct types: intimacy groups (e.g., families and close friends, which are highly important and interactive), task groups (e.g., work teams, in which members share common goals and must coordinate their actions), social categories (e.g., groups defined by shared attributes such as gender or occupation), and loosely associated groups (e.g., people waiting at a bus stop; Lickel et al., 2000, 2001). These group types differ systematically in their typical relational structures and, consequently, provide distinct cognitive frameworks that perceivers use to process, organize, and store social information. In this sense, group type can activate group-related network schemas that guide how individuals learn and represent social networks. Task groups, which require coordination to achieve shared goals, are typically characterized by higher centralization and shorter path lengths (Johnson et al., 2006; Lickel et al., 2006). In contrast, social categories are defined primarily by shared attributes rather than interactional demands and therefore need not exhibit centralized or densely interconnected structures, often resulting in more fragmented networks.[1] Accordingly, individuals may possess cognitive network schema regarding how relationships among individuals are typically organized within that type of group. According to this schema, networks associated with task groups are expected to be densely connected and centralized, whereas networks associated with social categories are not (Zhang et al., 2025). Because this distinction is not strictly all-or-none in terms of structural parameters, it could be understood as continuous: Networks associated with task groups are

[1] Whereas intimacy groups are characterized by deeply intertwined kinship or friendship ties that tend to be stable over time, and loosely associated groups often lack enduring interpersonal connections, task groups and social categories afford greater flexibility in how relationships are formed and inferred. Hence, we focused on task groups and social categories.

expected to be more densely connected and more centralized than those associated with social categories. In this comparison, social categories can serve as a baseline for estimating schema strength, as reduced density and centralization do not imply the absence of connections. Given the central role of friendship ties in the construction of social networks (De Dreu et al., 2024), the present study focuses on friendship relations and proposes that such group-related network schemas shape how people learn and represent social networks.

If group-related schemas contribute to the learning of social networks, then the encoding and retention of new relational information should be influenced by the extent to which that information conforms to preexisting schematic expectations. Consistent with prior accounts of schema-based learning, information that aligns with an activated schema reduces cognitive load and facilitates encoding and retrieval, thereby enhancing learning and memory performance (Sweller, 1988, 2011). Accordingly, we predict a matching effect, whereby memory for social relationships is enhanced when the structure of the learned network aligns with the schema activated by the corresponding group type (e.g., relationships from a dense and centralized network are remembered more accurately when described as being from a task group). Critically, if group-related network schemas shape network learning, we further hypothesize that the magnitude of the matching effect would be determined by the strength of the underlying schema. Although a matching effect has been reported in prior work (Zhang et al., 2025), existing studies have not established whether this effect is causally attributable to group-related network schemas. The present research addresses this gap by combining correlational analyses with experimental manipulations to directly examine how the strength of network schemas shapes the learning and memory of social networks.

Four experiments were conducted. Experiment 1 examined the existence of group-related network schemas and their contribution to learning and memorizing social networks by assessing the association between individual differences in schema strength and the matching effect. Because Experiment 1 was correlational in nature, Experiment 2 was designed to provide causal evidence by experimentally manipulating the strength of group-related network schemas through textual descriptions of within-group connectivity and examining their effects on memory performance. Experiment 3 tested the domain specificity of group-related network schemas by shifting to a nonsocial context—flight connections—to determine whether the typology-driven matching effect persists when the social element is removed.

Finally, Experiment 4 extended Experiment 1 by incorporating a computational modeling approach based on the *Successor Representation* (SR), which represents relational structure by encoding the expected future co-occurrence of states. Within this framework, social network representations are not limited to directly observed dyadic relationships but can also incorporate indirect, multistep connections (e.g., friends of friends). The SR model quantifies a successor discount parameter (γ), which indexes the extent to which learners engage in multistep abstraction when forming social networks (Son et al., 2023, 2024). Critically, γ determines the degree to which such multistep relations are integrated: Lower values emphasize local, one-step associations, whereas higher values reflect more abstract and globally structured representations that incorporate information across multiple relational steps. By integrating behavioral memory measures with computational modeling, the present set of experiments aims to elucidate how group-related network schemas shape the learning and representation of social networks.

Experiment 1

Group-related network schemas were assessed in the absence of any learned network information. Specifically, participants were asked to infer a fixed number of potential relationships among 10 group members based solely on group examples representing each group type. These examples were presented as group labels (e.g., "students working on group assignments" for task groups vs. "teachers" for social categories) and were selected from commonly used labels in prior research (Lickel et al., 2000; Zhang et al., 2025). Because no network structure was provided in this task, participants' constructions reflected their schematic expectations about how relationships are organized within each group type. Participants who generated networks showing greater structural differences between the two group types were therefore interpreted as possessing stronger group-related network schemas. The structural parameters implied by the group-related network schema were estimated from participants' inferred social networks in this task using two metrics—average shortest path length and degree centralization—which capture distinct global properties of social networks. Average shortest path length reflects overall network connectivity, with lower values indicating more closely interconnected individuals (Boguñá et al., 2020; Newman, 2010; Scott & Carrington, 2011). Degree centralization indexes the extent to which a network is organized around particular individuals, with higher values indicating the presence of prominent central members (Bernstein et al., 2022; Freeman, 1979). In this sense, the differences in structural parameters (i.e., average shortest path length and degree centralization) between the constructed networks provide a behavioral index of the strength of the network schematic distinction between the two group types.

After generating social networks, participants were also asked to learn and memorize social networks that either aligned or misaligned the network schema activated by the label for each group type. In this case, memory performance would be enhanced when the learned network structure aligned with the activated schema (i.e., a matching effect), and the magnitude of this effect would be predicted by the strength of the underlying group-related network schema.

Method

Transparency and Openness

In line with the Journal Article Reporting Standards, we report our sample-size determination, any data exclusions, and all manipulations and measures (Kazak, 2018). All experiments in the "Social Network Cognition" project were approved by the Department of Psychology Research Ethics Board at the authors' university and conducted in accordance with relevant guidelines and regulations. All data and analysis code are publicly available on the Open Science Framework at https://osf.io/bya7s/overview?view_only=124feb5ac48f4e94949eaf01bb4bc6d9. None of the experiments was preregistered.

Participants

We determined the planned sample size using G*Power 3.1 (Faul et al., 2007). To detect whether group type influences memory performance for different network types in a within-subjects design—assuming a medium effect size (d = 0.5), an α level of .05, and a power of .80—the minimum required sample size was calculated at

34 participants. However, to accommodate the counterbalancing of experimental materials across eight versions and ensure equal distribution, we set the target sample size at 40 valid participants. This sample size is consistent with previous studies investigating similar research questions (Zhang et al., 2025).

Ultimately, 44 participants were recruited for the study. Three participants failed the attention check task and were therefore excluded. Consequently, data from a total of 41 participants were included in the final analysis. The final sample consisted of 25 men and 16 women ranging in age from 18 to 26 years (M = 21.51, SD = 2.12). All participants were of Han ethnicity. Participants were compensated approximately 40 RMB for completing the experiment.

Experimental Stimuli

Instead of presenting abstract definitions of group types, we used commonly used group labels drawn from prior research to illustrate them (Lickel et al., 2000; Zhang et al., 2025). Following the methodology of Zhang et al. (2025), we selected the two most representative labels (i.e., those with the highest frequency) for each group type to serve as stimuli. For task groups, the labels “coworkers” and “students working on group assignments” were chosen, whereas for social categories, “teachers” and “civil servants” were selected. Based on established definitions (Lickel et al., 2000), labels such as “students working on group assignments” and “coworkers” typically imply interaction patterns organized around coordination toward shared goals, characteristic of task groups. In contrast, labels such as “teachers” or “civil servants” denote shared attributes or occupational identities, representing social categories that emphasize common identity rather than a specific joint task. These labels were employed to activate the relevant group schemas. In some real-world contexts, groups such as teachers or civil servants may also exhibit central members. However, our manipulation was designed to capture general schematic expectations about relational structure that people tend to associate with different group types, rather than to reflect specific possible instance of these groups.

Meanwhile, the two most representative social networks for each group type were adopted from Zhang et al. (2025). The social networks for task groups were characterized by shorter average shortest path lengths and higher degree centralization. Conversely, the social networks for social categories were characterized by longer average shortest path lengths and lower degree centralization (see Supplemental Figure S1 for more details). Using these four group labels and four social networks, we employed a pseudorandom method to generate eight predetermined combinations as experimental stimuli, which were counterbalanced across participants (please refer to Supplemental Table S2).

The group members’ names were constructed using the top 40 Chinese surnames from the “100 surnames” list for 2020 (Ministry of Public Security, PRC, 2021). These surnames included 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). To standardize the memory load, the given name was uniformly replaced by “Mou (某)” (a Chinese placeholder for “unknown entity”). This resulted in 40 unique names, such as Li Mou (李某). To balance typicality and familiarity, group member names were counterbalanced across the four experimental groups, with each group containing the top five and bottom five surnames (see Supplemental Table S3).

Procedure and Design

Stimuli were presented on a 15.6-in. LED monitor (1,920 × 1,080 resolution, 120 Hz refresh rate) at a 60-cm viewing distance. Custom software developed in PsychoPy 3.0 was used for presentation. The experiment involved two main tasks: generating social networks, in which participants inferred potential relationships among 10 group members based solely on the presented group label with no preexisting network structure provided, and memorizing social networks, in which participants were instructed to learn the relationships among 10 persons within a group as accurately as possible for a subsequent memory test.

Generating Social Networks. Participants first read the task instructions (see the Supplemental Material) for at least 30 s and then began the experiment by pressing the space bar. They were asked to infer potential friendships among 10 group members. As shown in Figure 1, a group type description and how to construct a social network appeared at the top of the screen, followed by images of 10 individuals, with participants informed that 12 pairs of them were friends. Participants dragged all figures into the panel and created connections by left-clicking one figure and right-clicking another; double-clicking a line deleted it. They could freely adjust figure positions before clicking “Finish” to continue. Four group labels were used (two task groups, two social categories), with order counterbalanced via a Latin square. A practice trial using the label “people in a tour group” familiarized participants with the task. The experiment lasted about 30 min.

Afterward, participants completed an attention check asking them to select all four group labels shown during the experiment from a list with eight options. Those who failed the check were excluded.

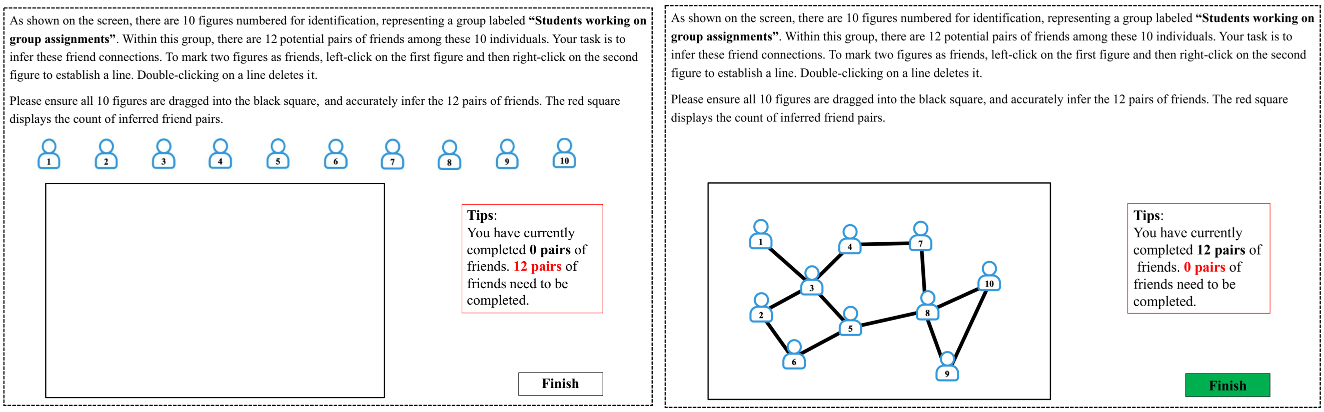
Memorizing Social Networks. This task consisted of two phases within each block: the learning phase and the test phase (Figure 2). The experiment used a within-subjects design with two factors: network type (task group vs. social category; the structure learned) and group type (the label shown). Each of the four combinations was presented in one block, and block order was randomized. In this case, when the learned network was described using the same group type label that had been used to generate it, the structure aligned with the activated schema; otherwise, it was misaligned.

In the learning phase, participants viewed 45 pairs representing all relationships among 10 group members and completed two randomized learning rounds (90 trials total). After a 5-min break, they proceeded to the test phase. In each block, only 10 of the 45 dyads represented friendships, but participants were not told this. A practice session (not recorded) familiarized participants with the procedure. Each trial began with a 500-ms fixation cross, followed by two stick figures labeled with names and shown for 3,000 ms. Their relationship (“X and Y: friendship/no relationship”) appeared below the figures, and a group label was displayed at the top. After each trial, a 500-ms blank screen appeared. All pairs were presented in random order, and participants could take a brief break every 15 trials.

The test phase mirrored the learning phase with two key changes: The relationship text was removed, and only the response options (“F: friendship; J: no relationship”) were shown. Participants judged

Figure 1

Interface for Generating Social Networks



Note. The figure shows the interface used by participants for generating social networks. It illustrates the blank starting screen (left panel) and a completed network structure (right panel). See the online article for the color version of this figure.

whether the presented pair had a friendship based on their memory, pressing "F" for friendship and "J" for no relationship. Responses were required within 3,000 ms, and no feedback was provided.

Data Analysis

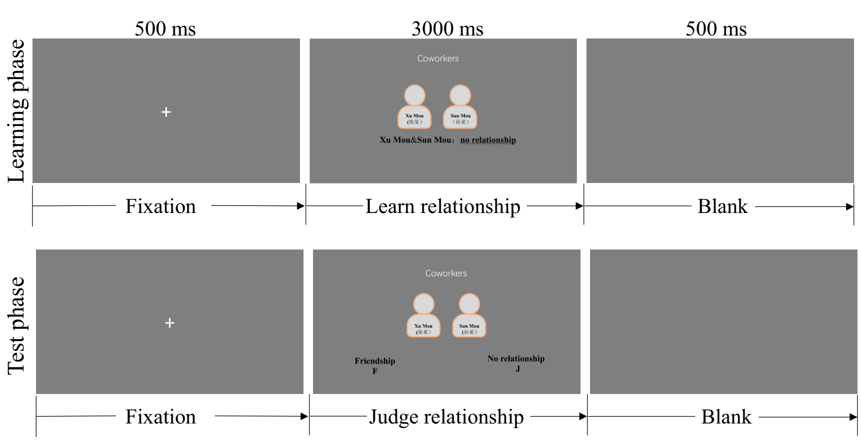
For the task of generating social networks, we computed the average shortest path length and degree centralization for each participant's constructed network. Average shortest path length reflects how separated individuals (nodes) are, with smaller values indicating closer connections (Boguñá et al., 2020; Newman, 2010; Scott & Carrington, 2011). Degree centralization measures how much the network centers on particular individuals, with higher values indicating stronger centralization (Bernstein et al., 2022; Freeman, 1979). The formulas for both metrics are provided in the Supplemental Material.

For the memory task, accuracy was calculated as the proportion of correctly recalled friendships (K/N), where K is the number of correctly remembered friendship pairs and N is the total number presented during learning. Response times were also recorded for exploratory analyses.

All analyses were conducted in R Version 4.4.1 (R Core Team, 2023), using the packages igraph (2.1.1; Csardi & Nepusz, 2006), bruceR (2024.6; Bao, 2025), and ggplot2 (4.0.1; Wickham, 2016). Following the suggestions of Lakens (2013), we reported 90% confidence intervals for ANOVA effect sizes η_p^2 and 95% confidence intervals (CI) for effect sizes associated with t tests.

Figure 2

Trial Sequence for the Learning and Test Phases



Note. In the learning phase, participants viewed two figures along with their relationship (e.g., "XX and XX: friendship/no relationship") and a label at the top of the screen indicating the group type of the pair. They were instructed to memorize these relationships. In the test phase, participants were required to judge the relationship between the two individuals based on their memory from the learning phase. See the online article for the color version of this figure.

Results

Generating Social Networks

The results (Figure 3) showed that the average shortest path length was significantly lower in task groups (M = 2.050, SE = 0.038) than in social categories (M = 2.169, SE = 0.036), $t(40) = -3.056$, p = .004, Cohen's $d = -0.48$, 95% CI of d [−0.79, −0.16]. In contrast, degree centralization was significantly higher in task groups (M = 0.302, SE = 0.024) than in social categories (M = 0.190, SE = 0.016), $t(40) = 4.08$, $p < .001$, Cohen's d = 0.64, 95% CI of d [0.32, 0.95]. These findings indicate that, relative to social categories, task groups are constructed as having denser connections and more pronounced centrality within their social networks.

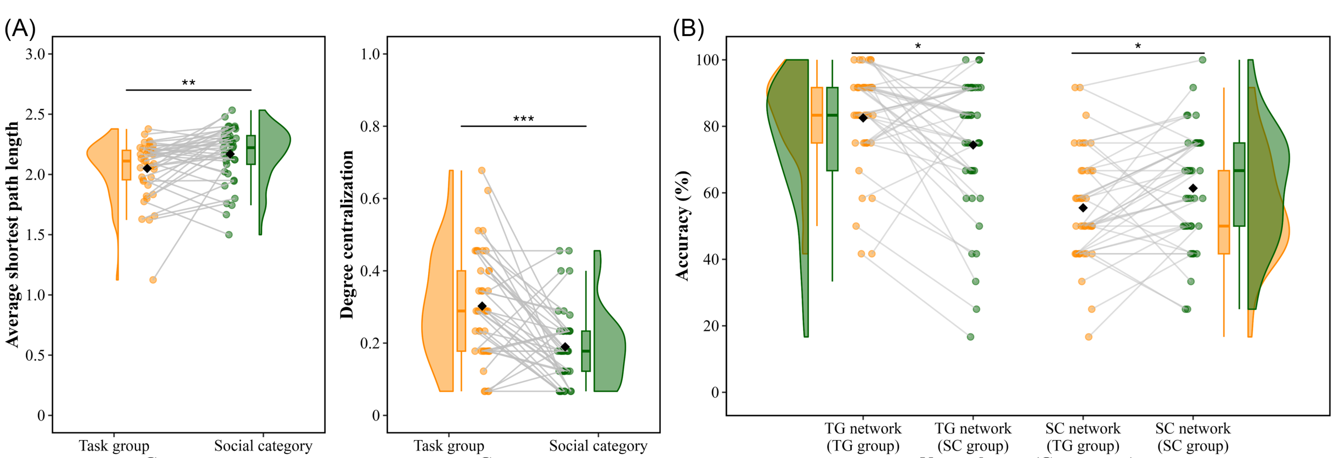
Memorizing Social Networks

Figure 3 presents the memory accuracy for friendships. The accuracy data were submitted to a 2 (*network type: task group vs. social category*) × 2 (*group type: task group vs. social category*) repeated-measures analysis of variance. The analysis revealed a significant main effect of network type, $F(1, 40) = 58.57$, $p < .001$, $\eta_p^2 = 0.59$, 90% CI of η_p^2 [0.43, 0.71], indicating higher accuracy of memorizing social relationships from the task-group networks (M = 78.5%, SE = 2.3%) than from the social-category networks (M = 58.4%, SE = 2.3%). The main effect of group type was not significant, $F(1, 40) = 0.37$, p = .548, $\eta_p^2 < 0.01$, 90% CI of η_p^2 [0.00, 0.11]. Importantly, the interaction between network type and group type was significant, $F(1, 40) = 9.82$, p = .003, $\eta_p^2 = 0.20$, 90% CI of η_p^2 [0.05, 0.37]. Simple effects analyses showed that, for networks originally generated from task groups, memory accuracy was higher when they were described as being from task group (M = 82.5%, SE = 2.4%) than when described as being from social category (M = 74.4%, SE = 3.2%), $t(40) = 2.59$, p = .013, Cohen's d = 0.40, 95% CI of d [0.09, 0.71]. Conversely, for networks originally generated from social categories, memory accuracy was lower when they were described as being from task group (M = 55.5%, SE = 2.6%) than when described as being from social category (M = 61.4%, SE = 2.7%), $t(40) = -2.23$, p = .031, Cohen's d = 0.29, 95% CI of d [−0.55, −0.03]. Overall, these results demonstrate a matching effect: Memory accuracy is higher when the provided group label aligns with the group type from which the network was originally generated than when they are misaligned.

Relation Between Generating and Memorizing Social Networks

To examine whether group schemas about social networks contribute to the matching effect, we constructed an index of group schema strength based on participants' task of generating social networks. Specifically, we computed two indices of schema strength: (a) the difference in average shortest path length calculated as social-category networks minus task-group networks (with lower average shortest path length indicating denser connectivity) and (b) the difference in degree centralization calculated as task-group networks minus social-category networks. We then correlated these indices with the magnitude of the matching effect, computed as the difference in memory accuracy between aligned and misaligned network structures, calculated separately for task groups and social categories, and then averaged across the two group types to obtain a single index for each participant. Results revealed a significant positive correlation between group schema strength and the matching effect (average shortest path length: r = 0.33, p = .037, 95% CI [0.02, 0.58]; degree centralization: r = 0.33, p = .036, 95% CI [0.02, 0.58]; see Figure 4). This suggests that stronger group schemas enhance memory accuracy for social relationships within those schemas.

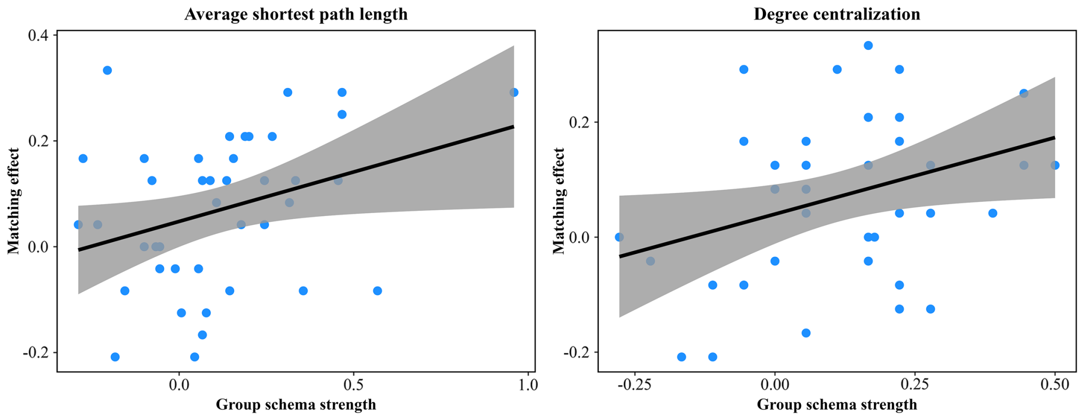
Figure 3
Results of Generating and Memorizing Social Network in Experiment 1



Note. Panel A shows the average shortest path length and degree centralization for different group types. Panel B shows the memory accuracy by network type and group type. Diamonds represent the mean for each condition. SC = social category; TG = task group. See the online article for the color version of this figure.
* p < .05. ** p < .01. *** p < .001.

Figure 4

Correlation Between Group Schema Strength and the Matching Effect in Experiment 1



Note. Each point represents a participant. Solid lines indicate the fitted linear regressions, and shaded bands represent the 95% confidence intervals. See the online article for the color version of this figure.

Experiment 2

Because Experiment 1 was correlational in nature, it could not establish whether the observed matching effect during learning social networks was causally driven by group-related network schemas. Experiment 2 was therefore designed to provide causal evidence by directly manipulating the strength of these schemas. Building on the procedure of Experiment 1, we experimentally strengthened or weakened group-related network schemas through explicit textual descriptions of within-group connectivity and centralization prior to network generation and learning. Specifically, the reinforcing condition presented structural differences consistent with the schema (i.e., task-group networks that were relatively dense and centralized compared with social-category networks), whereas the attenuating condition reduced the structural differences between the two group types, thereby weakening the schematic expectations. By reinforcing or attenuating schematic expectations associated with task groups and social categories, this manipulation allowed us to test whether changes in schema strength would systematically modulate memory performance for social relationships. If group-related network schemas play a causal role in network learning, then weakening the schema should attenuate or eliminate it.

Method

Participants

The sample size was determined similar to Experiment 1, with each group having at least 40 participants. Eighty-two participants were recruited, with two excluded for failing the attention check. Finally, a total of 80 participants participated in this experiment with each-between-subjects (strong schema vs. weak schema) having 40 participants and were compensated 40 RMB. The final sample consisted of 38 men and 42 women ranging in age from 18 to 28 years ($M = 22.16$, $SD = 2.33$).

Procedure and Design

This experiment followed the procedure of Experiment 1 with the modifications described below. In the task of generating social networks, additional textual information was presented above the group label to manipulate the strength of the group-related network schema. This text was displayed prior to the network construction screen for 60 s and remained visible at the top of the screen while participants generated networks. Given that the group-related network schema was defined as the expectation that social networks associated with task groups are more closely connected and more centralized than those associated with social categories, we manipulated whether the observed network structures reinforced or attenuated the structural differences implied by the schema.

In the strong schema condition, the descriptions were consistent with this schematic expectation. For the task group, the participants were told, “Members of this group are closely connected, and there are central members. The central members are linked to most other members and hold substantial influence within the network.” For the social category, the participants were told, “Members of this group are loosely connected, and there is no central member. The level of connectedness among members is largely uniform, and they hold comparable influence within the network.” These descriptions therefore reinforced the expected structural distinction implied by the schema between the two group types.

Simply reversing these descriptions would not appropriately weaken the schema, because doing so would create a contradictory structural pattern rather than attenuating the expected difference. The group-related network schema primarily specifies expected connectivity patterns for task groups, while the structure of social categories functions largely as a baseline for comparison. Therefore, to attenuate the schematic expectation, we used similar descriptions for both group types, thereby reducing the structural contrast that would normally be implied by group typology. In the weak schema condition, for the task group, the participants were told, “Members of this group are loosely connected, and there is no central member.

The level of connectedness among members is largely uniform, and they hold comparable influence within the network." For the social category, the participants were still told, "Members of this group are loosely connected, and there is no central member. The level of connectedness among members is largely uniform, and they hold comparable influence within the network."

These statements were shown again midway through the task of memorizing social networks to reinforce the manipulation. Because network schemas primarily apply to task groups, only task-group networks were included to keep the experiment at a reasonable duration.

Results

Validity of Group Schema Strength

In the strong schema condition (see Figure 5), similar to Experiment 1, the average shortest path length was significantly lower in task groups ($M = 2.050$, $SE = 0.038$) than in social categories ($M = 2.221$, $SE = 0.030$), $t(39) = -7.715$, $p < .001$, Cohen's $d = -1.22$, 95% CI of d [−1.54, −0.90], but the degree centralization was significantly higher in task groups ($M = 0.544$, $SE = 0.026$) than in social categories ($M = 0.103$, $SE = 0.010$), $t(39) = 15.11$, $p < .001$, Cohen's $d = 2.39$, 95% CI of d [2.07, 2.71]. However, in the weak schema condition (see Figure 6), there was no significant difference in the average shortest path length between task group ($M = 2.211$, $SE = 0.032$) and social category ($M = 2.254$, $SE = 0.024$), $t(39) = -1.35$, $p = .185$, Cohen's $d = -0.21$, 95% CI of d [−0.53, 0.11], nor in degree centralization (task group: $M = 0.114$, $SE = 0.017$; social category: $M = 0.100$, $SE = 0.012$), $t(39) = 0.94$, $p = .355$, Cohen's $d = 0.15$, 95% CI of d [−0.17, 0.47]. Together, these results validate the manipulation of schema strength.

Memorizing Social Networks

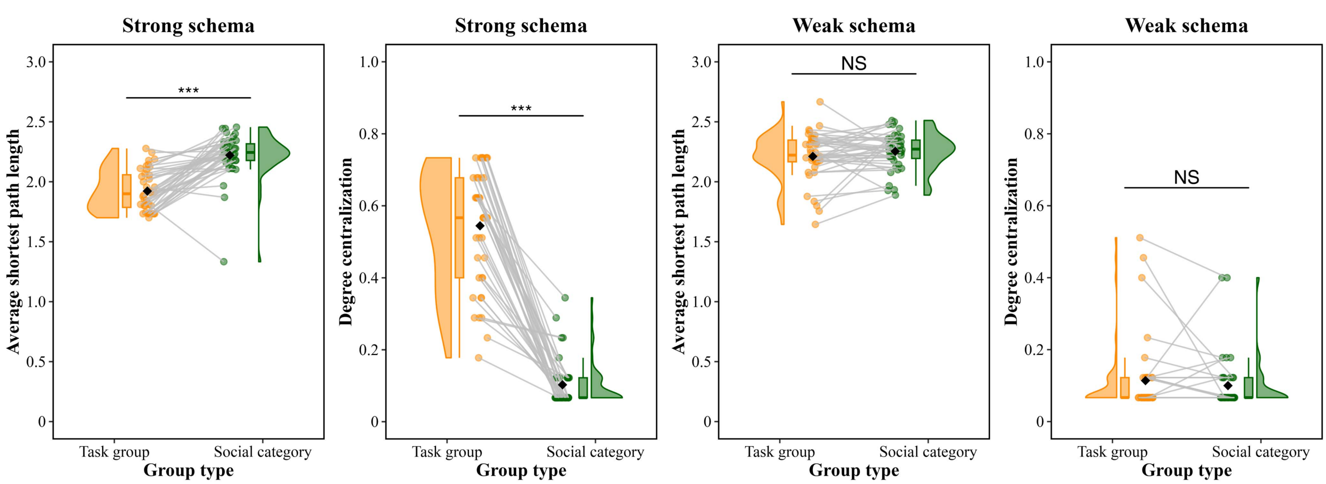
Figure 6 presents the memory accuracy for friendships as a function of schema strength and network type. Accuracy data were analyzed using a 2 (*schema strength: task group vs. social category; between subjects*) × 2 (*group type: task group vs. social category; within subjects*) mixed-design analysis of variance. The main effect of schema strength was not significant, $F(1, 78) = 1.50$, $p = .225$, $\eta^2_p = 0.02$, 90% CI of η^2_p [0.00, 0.10]. The main effect of group type was significant, $F(1, 78) = 15.56$, $p < .001$, $\eta^2_p = 0.17$, 90% CI of η^2_p [0.06, 0.29], indicating higher memory accuracy when networks were labeled as task groups ($M = 82.5\%$, $SE = 1.6\%$) than as social categories ($M = 73.6\%$, $SE = 2.2\%$). Importantly, the interaction between network type and group type was significant, $F(1, 78) = 6.51$, $p = .013$, $\eta^2_p = 0.08$, 90% CI of η^2_p [0.01, 0.19]. Simple effects analyses showed that under strong schema conditions, memory accuracy was higher when networks were described as task groups ($M = 87.3\%$, $SE = 2.3\%$) than as social categories ($M = 72.7\%$, $SE = 3.1\%$), $t(39) = 5.08$, $p < .001$, Cohen's $d = 0.80$, 95% CI of d [0.44, 1.16]. This difference was not significant under weak schema conditions (task group: $M = 77.7\%$, $SE = 2.8\%$; social category: $M = 74.6\%$, $SE = 3.2\%$), $t(39) = 0.91$, $p = .371$, Cohen's $d = 0.14$, 95% CI of d [−0.17, 0.45]. These results again demonstrate a schema-based matching effect.

Experiment 3

Experiment 3 examined the domain specificity of group-related network schemas by shifting from a social context to a nonsocial domain—airports and flight connections—which was used in previous studies (Schwyck et al., 2025). Using an otherwise identical learning and memory paradigm, interpersonal friendships were replaced with flight connections between airports, with group membership defined by assignment to structured airport sets and corresponding group labels retained. This design allowed us to test whether the typology-driven matching effect observed in prior experiments depends on inherently social content or instead reflects a more general sensitivity to structural alignment. If group-related network schemas are specific to

Figure 5

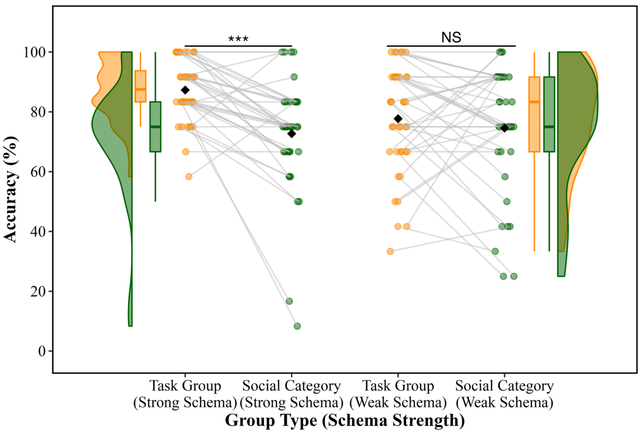
Average Shortest Path Length and Degree Centralization Between Group Types Under Different Schema Strength Conditions



Note. Diamonds represent the mean for each condition. NS = not significant. See the online article for the color version of this figure.
*** $p < .001$.

Figure 6

Memory Accuracy Between Group Types Under Different Schema Strength Conditions in Experiment 2



Note. Diamonds represent the mean for each condition. NS = not significant. See the online article for the color version of this figure.
*** $p < .001$.

social domain, then removing the social element should eliminate the matching effect, despite preserving comparable network structures and task demands.

Method

Similar to Experiment 1, 40 participants without exclusion completed the experiment and were compensated 40 RMB. This sample consisted of 18 men and 22 women ranging in age from 19 to 28 years ($M = 22.73$, $SD = 2.26$). The procedure and design were replicated from Experiment 1, with one key modification to shift the task to a nonsocial domain: The 10 group members were described as being located at different airports, and the relationship between individuals was defined by the presence of a direct flight between their airports ("having a direct flight" or "no direct flight").

Results

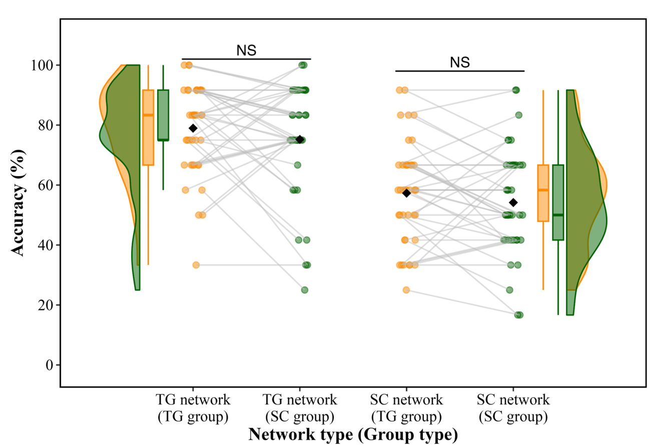
Figure 7 presents memory accuracy for flight connections. The accuracy data were submitted to a 2 (*network type: task group vs. social category*) × 2 (*group type: task group vs. social category*) repeated-measures analysis of variance. The analysis revealed a significant main effect of network type, $F(1, 39) = 81.56$, $p < .001$, $\eta_p^2 = 0.68$, 90% CI of η_p^2 [0.53, 0.77], indicating higher memory accuracy of flight connections learned from the task-group networks ($M = 77.1\%$, $SE = 2.2\%$) than from the social-category networks ($M = 55.7\%$, $SE = 2.4\%$). The main effect of group type was not significant, $F(1, 39) = 2.81$, $p = .102$, $\eta_p^2 = 0.07$, 90% CI of η_p^2 [0.00, 0.22], nor was the interaction between network type and group type, $F(1, 39) = 0.03$, $p = .864$, $\eta_p^2 < 0.01$, 90% CI of η_p^2 [0.00, 0.05]. Thus, when memorizing nonsocial connections, the matching effect disappeared, suggesting that group schemas play a specific role in memory for social relationships.

Experiment 4

Experiment 4 extended Experiment 1 by integrating a computational modeling approach based on the SR to directly characterize the learning and representational consequences of group-related network schemas. For any pair of network members, the SR encodes the expected likelihood that they will be observed together. In this approach, the SR estimates future co-occurrence by incrementally updating relational expectations based on experience. Learning is not limited to directly observed interactions; instead, newly acquired information is propagated through the network, allowing indirect relationships to influence predictions. For instance, observing an interaction between individuals A and B increases the predicted likelihood that A and B will be encountered together again, while also shaping expectations about individuals connected to B through additional relational steps (e.g., friends-of-friends and higher order connections). The contribution of these indirect pathways diminishes with distance and is controlled by the successor discount parameter, $\gamma \in [0, 1)$, which determines the extent to which multistep relationships are incorporated and thus the overall level of abstraction in the network representation. When $\gamma = 0$, the model reduces to pure memorization of one-step relations, whereas higher γ values reflect increasing reliance on multistep abstraction and yield a more integrated global representation of social structure. It has been suggested that people rely on the SR to form representations of social networks (Son et al., 2023, 2024). From this perspective, when the learned network structure aligns with the activated group-related schema, newly learned relationships can be efficiently integrated into a coherent global representation. In contrast, when the learned network structure violates schema-consistent expectations, individual dyadic relations are more difficult to integrate into the broader network structure. As a result, learners are more likely to rely on the memorization of one-step relations, engage in less multistep abstraction, and form more fragmented social network representations. This reduced abstraction is reflected in lower values of the successor discount parameter γ.

Figure 7

Memory Accuracy by Network Type and Group Type During the Memorization of Nonsocial Relations in Experiment 3



Note. Diamonds represent the mean for each condition. SC = social category; TG = task group; NS = not significant. See the online article for the color version of this figure.

Method

Participants and Design

Forty-one participants were recruited, with one excluded for failing the attention check. Finally, 40 completed the experiment and received 40 RMB as compensation. This sample consisted of 16 men and 24 women ranging in age from 18 to 29 years ($M = 22.15$, $SD = 2.47$).

The procedure and design largely followed the task of memorizing social networks in Experiment 1, with modifications to the learning phase to estimate parameters of the SR model (Son et al., 2023). Specifically, only task-group networks were included. Participants learned only friendship pairs, each presented twice across two blocks, with a group label displayed at the top of the screen. The test phase was identical to that of Experiment 1.

SR Model

In addition to memory accuracy, we modeled multistep abstraction using a reinforcement-learning–based SR algorithm (Dayan, 1993). We used the same steps as Son et al. (2023) to construct the SR model. The SR provides a computational account of how learners integrate local relational experiences into a broader network representation by encoding the expected discounted future co-occurrence of states. Given a network of N members, the SR can be represented as an $N \times N$ matrix M, in which each entry M_{ij} reflects the expected probability of observing member j after observing member i. In the present context, each network member corresponds to a state, and the SR captures not only direct relationships (e.g., A–B) but also indirect, multistep relationships (e.g., A–C via B). Importantly, M_{ij} captures not only the probability of a direct one-step transition from i to j but also the multistep likelihood of beginning at i and eventually reaching j through intermediate network members (e.g., friends-of-friends; $i \rightarrow k \rightarrow j$). In social networks, a useful heuristic is that j will be represented as more likely to be connected to i when the two individuals share a greater number of mutual friends.

The SR is updated according to standard reinforcement-learning procedures (Dayan, 1993; Russek et al., 2017; Stachenfeld et al., 2017), with minor modifications (Equation 1). Observations of friendship are encoded as a one-hot vector $1(j)$, that is, a vector of length N containing zeros except for a value of 1 at index j. This vector drives a row-wise update of M, scaled by a learning rate α. The successor discount parameter $\gamma \in [0, 1)$ causes the representation of state i to become more similar to its successor j by adding a fractional amount of M_j. This successor term, $\gamma > 0$, allows the SR to integrate information across multiple one-step transitions, thereby capturing multistep relational abstractions. This reinforcement-learning implementation was used to model the experiment:

$$M_i \leftarrow M_i + \alpha\delta,$$
$$\delta = 1(j) + \gamma M_j - M_i. \tag{1}$$

In implementations, the raw entries of the SR matrix represent the expected number of times a particular network member would be encountered during a random walk of length k. To convert these values into transition probabilities, the matrix was scaled by $(1 - \gamma)$. The parameter γ can also be interpreted as a lookahead horizon, corresponding to the number of steps integrated over during inference. Notably, the lookahead horizon increases exponentially as γ approaches 1. Consequently, small numerical differences in γ can correspond to substantial differences in the effective depth of multistep abstraction.

To translate the SR into probabilistic judgments of friendship, the model estimates weights that increase or decrease the contribution of SR-based predictions. Conceptually, this procedure is equivalent to estimating a softmax temperature parameter or a regression coefficient in logistic regression. Because agents may rely on multiple representational strategies, we allow for a mixture-of-experts framework in which different strategies jointly contribute to network representation. This is implemented using a logistic choice rule (Equation 2) that operates on a weighted linear combination of representational components (Equation 3).

The model allowed the successor discount parameter γ to vary freely across its theoretically defined range, $\gamma \in [0, 1)$. Free parameters, including γ and the mixture-of-experts weights, were estimated with the Nelder–Mead algorithm implemented in R's default optimizer, and model likelihoods were calculated using a logistic loss function. To ensure that the softmax function could fully saturate, all weights were multiplied by a constant scaling factor of 10, as the raw values in the SR matrix represent transition probabilities and are therefore small in absolute magnitude. The mixture-of-experts weights were regularized with an L2 penalty ($\sigma = 5$), such that an additional term, $\sum_i \lambda w_i^2$, was added to the log-likelihood, where $\lambda = 1/\sigma^2$. The data for each participant were fit independently, and each model was reestimated 25 times with different initializations; only the parameter estimates corresponding to the highest likelihood were preserved:

$$f(x) = \frac{1}{1 + exp(-x)}, \tag{2}$$

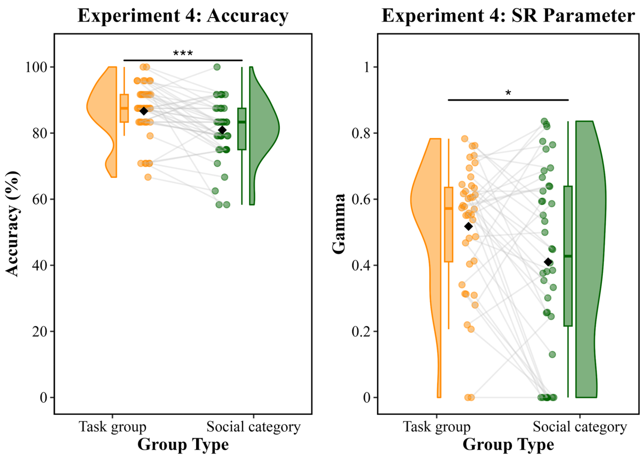
$$p(\text{relation}) = f(\beta_0 + \beta_1 SR + \cdots). \tag{3}$$

Importantly, when compared with the triad completion schema model and the community schema model, the SR model consistently outperformed both across all values of γ (see the Supplemental Material for details).

Results

Figure 8 displays memory accuracy for friendships and the successor discount parameter. A paired t test showed higher memory accuracy when friendships were described as task groups (M = 86.7%, SE = 1.4%) than as social categories (M = 80.9%, SE = 1.4%), $t(39) = 4.06$, $p < .001$, Cohen's $d = 0.64$, 95% CI of d [0.32, 0.96], again demonstrating the matching effect. Further, γ parameter when friendships were described as task groups ($M = 0.518$, $SE = 0.031$) was significantly higher than when described as social categories ($M = 0.410$, $SE = 0.045$), $t(39) = 2.60$, $p = .013$, Cohen's $d = 0.41$, 95% CI of d [0.09, 0.73]. These findings indicate that describing the social network as a different group type results in less abstract and less integrated network representations, as reflected in lower successor discount parameters.

Figure 8
Memory Accuracy and SR Parameter (γ) by Group Type in Experiment 4



Note. Diamonds represent the mean for each condition. SR = Successor Representation. See the online article for the color version of this figure.
$^{*} p < .05$. $^{***} p < .001$.

Discussion

Across four experiments, the present research provides converging evidence that group-related network schemas systematically shape how people learn and represent social networks. Experiment 1 demonstrated that participants possess preexisting schemas about the social network structure of different group types and that these schemas predict a matching effect in memory: Social relationships are remembered more accurately when the learned network structure aligns with the schema activated by the group type. Experiment 2 extended this finding by causally manipulating schema strength, showing that weakening group-related schemas correspondingly attenuated the matching effect. Experiment 3 established the domain specificity of this phenomenon by demonstrating that the matching effect disappears in a nonsocial domain (flight networks), despite comparable structural properties and task demands. Finally, Experiment 4 showed that schema–structure alignment shapes the computational form of network representations, as indexed by higher successor discount parameters (γ) in the SR model, reflecting greater multistep abstraction and more integrated global representations. Together, these findings indicate that group-related network schemas exert a robust, causal influence on social network learning.

One alternative interpretation of these findings is that they merely reflect differences in perceived groupness or entitativity between task groups and social categories. However, previous studies reported that the entitativity was perceived as higher in social categories than task groups (Zhang et al., 2025), and further several aspects of the present results argue against a purely entitativity-based account. First, the matching effect depended on structural alignment, not simply on group labels: Memory advantages emerged only when the learned network structure matched the schema implied by the group type. Second, Experiment 2 showed that manipulating schema strength through explicit relational descriptions altered memory performance, even though the group labels themselves—and their associated entitativity—remained unchanged. Third, Experiment 3 demonstrated that similar group labels applied in a nonsocial domain did not produce matching effects, suggesting that the phenomenon is not driven by general assumptions of cohesion or unity. These findings indicate that group-related schemas encode expectations about relational structure, rather than merely reflecting global impressions of groupness.

The present work contributes to the literature on learning social networks by clarifying how people move from local relational information to global structural representations. Previous research has emphasized local heuristics—such as triadic closure—as mechanisms for inferring missing ties (Brashears, 2013; Flynn et al., 2010; Janicik & Larrick, 2005). The current findings extend these accounts by showing that such local schemas are embedded within broader, group-level network schemas that organize learning from the outset. Rather than incrementally accumulating isolated dyadic facts, learners appear to interpret new relationships through schemas that specify expected global properties—such as centralization and overall connectivity—thereby enabling efficient integration of local observations into coherent network representations. This perspective is consistent with prior evidence demonstrating that global network structure influences social network learning. For instance, people often assume that individuals who belong to the same group are connected even when such ties are not present (Freeman & Webster, 1994; Son et al., 2023). In addition, individuals who serve as brokers in their own social networks—linking otherwise unconnected others—show an advantage in learning and recalling networks that mirror common real-world structures, but not those with atypical or unfamiliar configurations (Schwyck et al., 2025). Such findings suggest sensitivity to global structural regularities in social networks. Crucially, however, the present results extend this work by showing that these structural expectations are not governed by a single, universal template, but instead are modulated by group typology. In this sense, group-related network schemas function as structural priors, guiding how new social information is encoded, organized, and retrieved.

The current finding does not indicate that all task groups must be centralized or that all social categories must lack centralization. Rather, the schema reflects a general expectation about typical relational organization. Counterexamples are therefore possible—for instance, a social category that appears centralized or a task group that is relatively decentralized. Instead of specifying a fixed structural rule, the schema predicts differences in continuous structural parameters: On average, networks associated with task groups are expected to be more densely connected and more centralized than those associated with social categories. Given the presence of noise, this structural tendency does not necessarily imply fixed structural parameter and may fall within a range of values consistent with the general organizational patterns associated with each group type. An important direction for future research is to determine how group-related network schemas are formatted in the mind.

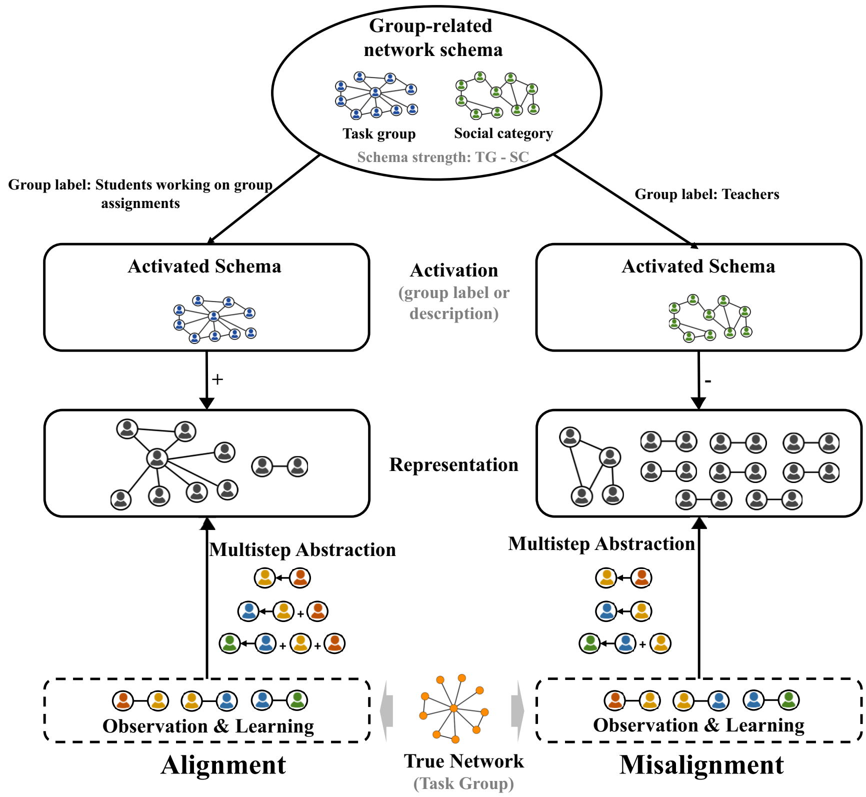
The findings of Experiment 3 further clarify the nature of group-related network schemas by establishing the domain specificity of learning social networks. When social relationships were replaced with nonsocial connections between airports, the typology-driven matching effect disappeared, despite the preservation of comparable network structures and equivalent learning and memory demands. This dissociation suggests that group-related network schemas are not generic structural templates applied indiscriminately across domains, but are instead tightly coupled to the interpretation of social relations. Consistent with this view, prior work has shown that social traits—such as social orientation and perspective taking—are specifically associated with learning social community structure, rather than structurally matched nonsocial communities (Tompson et al., 2019). At first glance, this conclusion may seem inconsistent with recent findings showing comparable memory performance when the same network was presented either as a friendship network or as a nonsocial network of flights between airports. (Schwyck et al., 2025). However, an important methodological distinction may reconcile these results. Whereas Schwyck and colleagues asked participants to memorize networks defined over airports themselves, the present study required participants to learn and remember group members located within airports, thereby preserving group-based representations even in the nonsocial domain. This difference suggests that the domain specificity of social network learning may depend on whether relational information is construed over social agents versus abstract entities. Identifying this boundary condition is crucial for understanding when social schemas are engaged and when learning relies primarily on domain-general structural mechanisms.

One likely reason is that group typology in the social domain carries rich semantic and functional meaning—such as expectations about coordination, influence, and interpersonal interaction—that directly constrain how relationships among individuals are construed. In contrast, group typology applied to nonsocial connections lacks comparable interpretive significance and therefore fails to use schemas that guide relational abstraction. These findings suggest that group-related network schemas may be preferentially engaged in the context of interpersonal relations, rather than operating uniformly over all graph structures. An alternative possibility is that the schema was not activated in the airport context because the materials were less familiar than everyday social groups, which might reduce the likelihood of engaging schema-driven processing. This is a reasonable possibility. However, we believe the airport context provides initial evidence that group-related network schemas are tied specifically to interpersonal relations. In the memorization task, the only difference between the social and nonsocial conditions was the type of relation connecting each pair (friendship vs. flight connection). The cognitive demands of memorizing these relations appeared comparable, as overall memory performance was similar across domains (task-group networks: 78.5% for friendship in Experiment 1 vs. 77.1% for flight connections in Experiment 3; social-category networks: 58.4% for friendship vs. 55.7% for flight connections). Moreover, the consistent difference between task-group and social-category networks indicates that participants organized the pairs into network structures even in the airport context; otherwise, performance should have been similar across network types, given that the number of pairs to memorize was identical. Importantly, flight connections between airports have been widely used as a nonsocial network analogy in prior research (Andrews et al., 2024; Schwyck et al., 2025). Nevertheless, differences in domain familiarity and prior knowledge may still influence whether schematic expectations are engaged. Possibly, group-related network schemas may be more readily engaged when relational information concerns social agents, where people possess richer prior knowledge about typical interaction patterns. Future research could test this possibility more directly by manipulating domain familiarity or examining other nonsocial networks for which participants have stronger structural priors.

The computational modeling results from Experiment 4 further illuminate the mechanisms through which group-related network schemas influence network learning. Using the SR framework (Son et al., 2023, 2024), we showed that schema–structure misalignment is associated with lower successor discount parameters (γ), indicating reduced engagement in multistep abstraction and a greater reliance on one-step relational memorization. This finding suggests that schemas shape the depth at which relational pairs are integrated into a network during learning itself. When a learned network conforms to an activated group-related schema, learners appear more willing—or more able—to incorporate indirect relations (e.g., friends-of-friends) into their representations, yielding a more unified and abstract map of social space. Conversely, when schema expectations are violated, representations remain more local and fragmented. These results extend prior SR-based accounts of social cognition by demonstrating that the degree of abstraction in social network representations is not fixed, but is systematically modulated by top-down schematic knowledge about group types (see Figure 9). Importantly, this does not imply that stronger schemas invariably promote greater abstraction without constraint. Excessive multistep abstraction could, in principle, lead to the inference of nonexistent relationships, thereby impairing memory accuracy. Accordingly, memory performance is not necessary to be linearly related to the level of multistep abstraction. Rather, our findings suggest that when the activated network schema aligns with the learned structure, multistep more efficiently integrated into a coherent network representation—an effect reflected in higher γ values.

Combined with the behavioral and computational findings, we propose a preliminary theoretical framework for how group-related network schemas influence social network learning (see Figure 9). At the level of schema activation, group labels or examples can activate corresponding network schemas (e.g., Experiment 1). For task groups, the activated representation tends to be relatively dense and centralized, whereas for social categories, it is less so. In this process, social categories can be considered a baseline. Accordingly, schema strength primarily reflects the structure difference, especially the direction and extent of the activated structure for task groups. This interpretation is supported by the correlation analyses reported in the Supplemental Materials: Schema strength significantly predicted the matching effect for task groups but not for social categories. Consistent with this account, schema activation can be reinforced by descriptions consistent with the expected structure difference or attenuated by descriptions that weaken this expectation, primarily through manipulating structural descriptions associated with task groups (e.g., Experiment 2). At the level of learning, participants observe dyadic relations and rely on multistep abstraction to integrate these pairs into a coherent network representation. In the absence of schematic guidance, the same learned network (i.e., true network in Figure 9) should yield similar representations and performance across conditions. However, when a group-related schema is activated, it provides a top-down constraint that determines whether the learned structure aligns with the expected organization. When alignment occurs, the schema facilitates multistep abstraction, enabling learners to integrate isolated pairs into a coherent network representation. In contrast, when the learned structure is misaligned with the activated schema, this conflict reduces the extent of multistep abstraction (as reflected in lower γ values in Experiment 4), leading to more fragmented representations. Because coherent network representations are more efficient than storing isolated dyadic pairs (Basyouni & Parkinson, 2022; FeldmanHall et al., 2025), aligned conditions require fewer cognitive resources and

Figure 9
How Group-Related Schemas Shape Social Network Representations via Multistep Abstraction



Note. SC = social category; TG = task group. See the online article for the color version of this figure.

yield better memory performance, thereby producing the observed matching effect. Importantly, this top-down constraint based on the activated group schema appears to operate primarily in the social domain (Experiment 3).

An important open question concerns how group-related network schemas are formed. One possibility is that these schemas emerge through long-term experience with different kinds of groups, as individuals repeatedly observe regularities in the relational structures associated with teams and social categories. Over time, such regularities may be abstracted into stable schemas that can be rapidly activated by group labels. Another possibility is that group-related schemas are culturally transmitted, embedded in shared narratives, institutional practices, and linguistic conventions that specify how different groups "typically" function. These accounts are not mutually exclusive: Experiential learning and cultural transmission may jointly contribute to the formation and maintenance of group-related network schemas. Future work examining developmental trajectories, cross-cultural variation, and learning dynamics across repeated exposures could help clarify the origins of these schemas.

Constraints on Generality Statement

Several limitations of the present research should be acknowledged. First, although we focused on task groups and social categories, other group types—such as intimacy groups or loosely associated aggregates (Lickel et al., 2001)—were not examined in depth, limiting the generality of the conclusions. Second, the networks used in the experiments were necessarily simplified relative to real-world social networks, raising questions about ecological validity. Third, although Experiment 3 supports domain specificity, additional nonsocial domains and hybrid contexts would further clarify the boundary conditions of group-related network schemas. Finally, the participant samples in the present studies consisted primarily of undergraduate students. Individuals with substantial work experience may possess different experiences with task groups, and it therefore remains an open question whether typology-driven network learning generalizes to nonstudent populations, such as individuals working in industrial or organizational settings.

Conclusion

In conclusion, the present research demonstrates that group-related network schemas play a central role in shaping how social networks are learned and represented. By integrating behavioral experiments, causal manipulations, and computational modeling, we show that group typology influences not only what people remember about social relationships but also how abstractly those relationships are encoded. These findings advance our understanding of social network cognition by highlighting the importance of schema-driven abstraction and by bridging local learning mechanisms with global representational structure.

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