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Gender, Network Recall, and Structural Holes

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ABSTRACT

Accurate recall of social networks is critical to individuals' success in organizations, as it enables them to leverage networks more effectively. Understanding whether men or women exhibit greater recall accuracy is particularly important given persistent gender inequalities in workplaces and the role of networks in shaping access to social resources and opportunities. We propose that women and men exhibit different levels of recall accuracy, which depend on the structural characteristics of the network. Specifically, women's greater reliance on the triadic closure mental schema—assuming a relationship between two individuals who are both connected to the same third party—enhances their recall accuracy in more cohesive networks with many closed triads but diminishes it in networks with more structural holes. Across three studies, including a demographically diverse sample representative of the US population, we confirm that women exhibit superior network recall accuracy on average and show that this advantage is contingent on network structure. This research advances our understanding of gender differences in network cognition and offers a potential cognitive explanation for women's underrepresentation in brokerage positions, which require recognizing open triads.

1 | Introduction

Remembering with whom one has (or does not have) a relationship, as well as whether these individuals are connected to each other, is fundamental to collective social life, both in organizations and beyond (Dunbar 2012; Simmel 1922). Accurately assessing an organization's social landscape is a source of power, enabling individuals to recognize coalitions, political alliances, and patterns of influence (Krackhardt 1990). Cognitive representations of networks also affect the social resources individuals can summon (Smith et al. 2012). Because people can act only on the networks they perceive and recall (Kilduff and Krackhardt 2008), accuracy in representing the social structures around them is essential for effective networking (Kuwabara et al. 2018), attaining valuable positions in organizational networks (Burt 1992), and engaging in deliberate social action (Balkundi and Kilduff 2006).

Given the critical role of network accuracy in organizational success, gender differences in network accuracy may shed light on persistent gender inequalities in workplaces. Although research has extensively examined individual differences in network acuity (for reviews, see: Brands 2013; Smith et al. 2020), the question of whether women or men are more accurate in their network perceptions remains unresolved. Experimental evidence from non-organizational contexts suggests that women may have superior network recall compared to men (see Brashears et al. 2016; Lampronti et al. 2025; Lee, Lease et al. 2022; Lee, Foote et al. 2017 for evidence from high school students). However, findings from organizational settings suggest minimal or no gender differences in network cognition (e.g., Brands et al. 2015; Brands and Kilduff 2014; Landis et al. 2018). Moreover, women are underrepresented in brokerage positions, often viewed as the most valuable social network positions within organizations

(Fang et al. 2015; Woehler et al. 2021), suggesting that even if women do have superior network accuracy than men, they do not always leverage this advantage.

To explain when and why gender differences in network recall accuracy emerge, we build on research showing that individuals rely on mental schemas—cognitive shortcuts that simplify the encoding and recall of complex social structures (Brashears 2013; De Soto 1960; Freeman 1992; Janicik and Larrick 2005). A widely documented structure-based schema is the *triadic closure mental schema* (henceforth, "closure schema"), which assumes a tie between two individuals who are both connected to a common third person, thereby completing a triad. This heuristic reflects a well-established empirical regularity: social networks tend to exhibit clustering and triadic closure (Granovetter 1973; Kilduff et al. 2008; Watts and Strogatz 1998). Because the closure schema aligns with such regularities, it reduces cognitive effort and enhances accuracy when recalling cohesive networks. However, in networks with more open triads—that is, structural holes (Burt 1992)—this schema may lead to systematic errors by incorrectly prompting inferences of ties where none exist. Thus, while the closure schema improves recall when the network structure supports it, it impairs recall when the structure deviates from its assumptions.

We propose that men and women differ in their use of the closure schema, and that this difference underlies variation in network recall accuracy. Specifically, we argue that women are more likely to rely on the closure schema because they are more frequently exposed to cohesive networks that reinforce its utility. Gender, as a social identity, shapes individuals' behaviors and cognition through socialization and structural positioning (Brands et al. 2022; Schmader and Block 2015). Women are socialized to be more communal (Ellemers 2018) and are more likely to engage in roles that emphasize relational maintenance, such as kin-keeping (Moore 1990; Rosenthal 1985), and cooperation (Eccles 1987). These experiences foster habitual use of the closure schema, which improves recall in dense networks. Because men are less consistently exposed to cohesive contexts, they may be less likely to rely on the closure schema when encoding social structure. As a result, we expect women to demonstrate superior recall accuracy in cohesive networks but to lose this advantage as structural holes increase.

We test our theory across three studies. In Study 1, we use a vignette method with a large, demographically diverse sample representative of the US population to show that women possess more accurate network recall than men. This study also provides initial evidence that women's recall advantage diminishes when identifying structural holes. In Study 2, we replicate and extend these findings by showing that women recall their own social networks more accurately than men in a naturalistic setting, where networks are typically dense. This strengthens the external validity of our key proposition. Finally, in Study 3, we use an experiment where individuals are randomly assigned to learn networks with varying degrees of closure and structural holes. In line with our theory, we demonstrate that women's network recall accuracy advantage depends on the structural characteristics of the network, while men's does not.

This paper makes two key contributions to the extant literature on networks and recall. First, we offer a theoretical explanation for when and why gender differences in network recall accuracy emerge. Specifically, we argue that women's greater reliance on the closure schema enhances their recall in cohesive networks with many closed triads but provides less benefit in networks with many structural holes. This perspective moves beyond identifying average gender differences to theorizing the conditions under which these differences are more or less likely to appear. In doing so, we clarify that the closure schema is a product of patterned exposure (rather than a cognitive default), shaped by socialized experiences with specific types of network structures. This also offers a cognitive account of women's underrepresentation in brokerage positions, which require recognizing and leveraging open triads. Second, we empirically validate the existence of a network recall advantage for women outside laboratory experiments. This work provides the first empirical evidence that women can identify social networks more accurately than men in a demographically diverse population representative of the US population (Study 1). We extend this finding to real-life social networks (Study 2), enhancing the generalizability of these findings. We can therefore expect that women are more accurate than men at apprehending and recalling social groups and relations in novel social situations (e.g., a new group, a new job), when these involve significant closure.

2 | Conceptual Development

Existing research provides mixed evidence regarding gender differences in network recall accuracy. Laboratory and educational studies suggest that women recall social networks more accurately than men. For example, Brashears et al. (2016) found that women performed better in vignette-based recall tasks involving undergraduate students, while Lampronti et al. (2025) replicated this finding in a sample of French business school students. Similarly, S. Lee et al. (2017) found that girls were more accurate than boys at recalling their classmates' social affiliations in a sample of 1481 seventh- and tenth-grade students in China. This result was later replicated by Lee, Lease et al. (2022) in a study of 400 third- through fifth-grade students in the United States. However, studies conducted in organizational settings often find minimal or no gender differences in network recall accuracy (Brands and Kilduff 2014; Landis et al. 2018). For instance, Brands and Kilduff (2014) found that men and women employed at the head office of a regional distributor of electronics components are equally likely to misperceive women's brokerage positions. Similarly, in a study of 211 media agency employees, Landis et al. (2018) found that gender was not a significant predictor of perceived brokerage opportunities.

The generalizability of these findings to larger and more diverse populations remains unclear. First, several samples primarily comprised teenagers or young adults, raising the possibility that age influences cognitive development and network recall accuracy (Lee, Lease et al. 2022). Second, Brashears et al. (2016) and Lampronti et al. (2025) examined highly selected samples of elite university or business school students, which may not represent working populations. Third, these educational studies involved participants whose "work" and "leisure" networks were contained within the same institutional environment. In contrast, adults often manage more fragmented networks that may be associated with different schemas. Finally, studies conducted in organizational settings typically focus on brokerage positions and are limited in their generalizability, as their findings often depend on the specific network position under study but also on the structure, culture, or context of a given organization.

Most importantly, these studies do not explain *why* women and men may differ in their network recall accuracy. Although Brashears et al. (2016) ruled out explanations based on gender priming, personality, working memory capacity, effort expended on the task, and even some forms of mental schemas (i.e., cognitive flexibility), they did not consider whether systematic gender differences in the use of specific mental schema may explain these patterns. To address this gap, we build on the literature examining the mental schemas individuals use to encode and recall social network information.

2.1 | Mental Schemas

Individuals use mental schemas—cognitive shortcuts that simplify the encoding and recall of information—to manage the cognitive complexity of recalling social network information (Brashears 2013; De Soto 1960; Freeman 1992; Janicik and Larrick 2005).[1] Mental schemas enable predictions about the existence (or absence) of relationships based on contextual information, including connections between other people. These schemas align with empirical regularities representing social norms of behavior prevalent in a context. For instance, the norm of reciprocity in human behavior corresponds to a mental schema of reciprocity, allowing individuals to assume a reciprocal friendship based on observing only one direction of the relationship. Conversely, the absence of reciprocity in a typically reciprocal relationship conveys substantial information, prompting individuals to focus on the surrounding social dynamics. In contrast, leadership or authority relationships are assumed to be directed and unreciprocated (Carnabuci et al. 2018; De Soto 1960) as a superior and a subordinate cannot logically command one another. Information congruent with mental schemas, such as reciprocal friendships or asymmetric authority relationships, is easier and faster to encode and recall (De Soto 1960). In contrast, deviations from established schemas are harder and more time-consuming to learn (De Soto 1960). Thus, mental schemas reduce the cognitive effort required to encode and recall patterns of social relations.

At least two types of mental schemas have been identified in the literature: cultural schemas, which reflect cultural expectations about how individuals belonging to certain groups (typically familial) should be linked, and structure-based schemas, which rely on learned regularities of network patterns (Brashears 2013). Because kin-based schemas are context-specific and less relevant in work organizations, where kin relationships are infrequent, we focus on structure-based mental schemas. The most prominent structure-based mental schema is the triadic closure mental schema (Brashears 2013; Brashears and Quintane 2015; Freeman 1992; Janicik and Larrick 2005). The closure schema is based on the concept of a closed triad- three individuals who are all connected to one another (Wasserman and Faust 1994). For example, consider a triad with Jun, Alex, and Nilam. If Jun is known to be friends with Alex and Nilam, the closure schema predicts that Alex and Nilam are also connected. If, however, Alex and Nilam are not connected, this triad is open due to the structural hole between them, centered on Jun. This mental schema is rooted in the empirical regularity that social networks often form clusters with closed triads (Granovetter 1973; Kilduff et al. 2008; Newman 2003; Son et al. 2023; Watts and Strogatz 1998). By allowing individuals to infer the presence of an unknown relationship based on two known relationships, the closure schema reduces the cognitive effort needed to recall densely connected groups, which is particularly relevant in organizational contexts where more cohesive networks are common.

While prior work has often framed closure as a default schema—one that individuals deploy in the absence of contrary evidence (e.g., Janicik and Larrick 2005)—we propose a more contingent perspective. Specifically, we argue that the strength and accessibility of closure schemas are shaped by individuals' repeated exposure to particular network structures. In this view, schemas are not innate or universally deployed but are reinforced through patterned social experience. This theoretical shift allows us to connect schema accessibility to social identity processes: individuals embedded in more cohesive networks are more likely to develop and rely on closure schemas over time.

2.2 | Gender Differences in the Use of the Closure Schema

If the strength and accessibility of mental schemas are shaped by repeated exposure to particular network structures, then systematic differences in exposure—such as those shaped by gendered socialization—should lead to systematic differences in schema use. We argue that women, compared to men, make more comprehensive use of the closure schema when encoding and recalling network information. Core to our theorizing is the conceptualization of gender not as a purely biological distinction, but as a socially constructed identity (Brands et al. 2022). Gender operates as a social identity—that is, as an element of individuals' self-concept that derives from their knowledge and awareness of what it means to be a woman or a man (Schmader and Block 2015). This knowledge of their gender identity emerges from socially constructed and shared understandings of the typical characteristics, traits, and behaviors of women and men (Diekman and Schmader 2024; Eagly and Steffen 1984; Schmader and Block 2015). As a social identity, gender shapes self-expression, leading to socialized differences between women and men in terms of their behaviors, emotions, and cognitions (Diekman and Schmader 2024; Wood and Eagly 2002). These gendered differences—particularly in relation to social behavior—result in a pronounced tendency for women to develop and deploy the closure schema more than men, influencing their recall of social networks.

First, women are socialized to be more communal and relationship-oriented than men (Ellemers 2018), such that women's relationships tend to be a more central component of their identities (Cross and Madson 1997; Halevy and Kalish 2022). For example, women often fulfill the role of "kin keepers," or individuals who maintain relationships within their family or extended family networks (Moore 1990).[2] As kin keepers, women not only sustain relationships with distant family members but also cultivate a sense of connectedness and ensure that family members keep in touch (Rosenthal 1985). Critically, by definition, kin relations enjoy considerable triadic closure, which presents women with more exposure to networks where a closure schema applies. Beyond family contexts, women demonstrate greater communality than men in organizational settings. Women tend to inhabit more cohesive, interconnected networks than men (Fang et al. 2021) and are often found to have larger networks (e.g., Moore 1990). The importance of relationships to women's sense of self affects their cognition, meaning that they tend to pay attention to, and develop schemas for, managing information about relationships, and as a result exhibit enhanced recall for relational information, relative to men (Cross and Madson 1997). Given that women's networks tend to be large and interconnected, these cognitive processes would likely require the deployment of cognitive shortcuts and in particular, the closure schema, to make the cognitive load more manageable.

Second, socialized gender differences in attitudes toward competition may also contribute to women's greater use of the closure schema, relative to men. Women tend to have more positive attitudes toward tasks with low levels of social comparison and competition, while men prefer tasks with higher levels of social comparison (Eccles 1987). This divergence in preferences likely corresponds with differences in the tasks each gender engages in and the skills they develop through repeated practice (e.g., see Gneezy et al. 2003, 2009). Consequently, women may learn to approach tasks with an expectation of in-group cooperation and solidarity, reducing the need to track structural holes and favoring dense, more cohesive networks. Supporting this argument, Lampronti et al. (2025) find that rivalry among competitors negatively affects women's network recall, limiting their ability to mobilize their networks and obtain network returns. In contrast, men may learn to approach tasks with an expectation of in-group competition, motivating them to track structural holes to gain advantage and avoid vulnerability, as well as an expectation of decreased cohesiveness in the network.

In sum, existing literature provides evidence that women are more likely than men to build and inhabit social networks characterized by cohesion and closure. These factors facilitate the development of the closure schema and encourage its application—assuming the existence of relationships that close a triad is a more reliable strategy for women than men in terms of building an accurate representation of their social environment.

2.3 | Gender, Closure Schema, and Network Recall

We argued earlier that a heightened reliance on the closure schema reduces cognitive effort and enhances recall accuracy for networks whose structure aligns with the schema. Consequently, we predict that women's greater use of the closure schema will result in more accurate recall of more cohesive networks characterized by numerous closed triads. However, this advantage is unlikely to extend to less cohesive networks, which feature many open triads, where the closure schema is less effective due to its inconsistency with the network's structure. In contrast, we do not expect men's recall accuracy to vary significantly across different network structures. Men rely less on the closure schema than women, even in more cohesive networks, because repeated exposure to structurally diverse networks may dilute the reinforcement of any single schema, inhibiting the consolidation of structure-consistent recall strategies. While men encounter cohesive networks, they are also frequently exposed to sparser and more competitive networks, which reduces the predictive utility of the closure schema. As a result, men's recall accuracy is less influenced by the alignment between the closure schema and network structure, reflecting their lower dependence on this schema for encoding and recalling social relationships.

Building on these arguments, we predict systematic gender differences in network recall accuracy that depend on the network structure. Specifically, women will exhibit greater accuracy than men when recalling more cohesive networks characterized by many closed triads, reflecting their reliance on the closure schema. Given that many real-world networks contain substantial closure (Feld 1981; Holland and Leinhardt 1971; Newman 2003; Snijders et al. 2006), this greater usage of the closure schema will often benefit women and manifest as enhanced network recall (consistent with existing experimental evidence). However, as networks become less cohesive, the utility of the closure schema diminishes, and the recall accuracy of men and women is expected to converge (consistent with organizational studies of gender-based accuracy). We also predict within-gender differences in recall accuracy. Women should recall more cohesive networks more accurately than less cohesive ones, consistent with their reliance on the closure schema. In contrast, men's recall accuracy should remain relatively stable across network structures, as their lower reliance on the closure schema makes them less sensitive to variations in cohesion.

In summary, we hypothesize:

Hypothesis 1. *Women will have more accurate recall of social networks than men.*

Hypothesis 2. *The effect of gender on network recall accuracy is contingent upon network structure, such that:*

Hypothesis 2a. *Women will recall more cohesive networks more accurately than less cohesive networks, whereas men will recall more cohesive networks as accurately as less cohesive networks.*

Hypothesis 2b. *Women will recall more cohesive networks more accurately than men, but there will be no gender difference between men and women in the recall of less cohesive networks.*

3 | Overview of Studies

We assessed the proposed relationship between gender and network recall in three studies. In Study 1 (N = 9614), we used a vignette design with a representative sample of the US adult population to assess gender differences in network recall accuracy. In Study 2 (N = 154), we used Cognitive Social Structure data from a field study to provide evidence of women's network recall accuracy advantage in a naturalistic environment. Finally, in Study 3 (N = 507), we used an experimental design to test whether gender differences in network recall

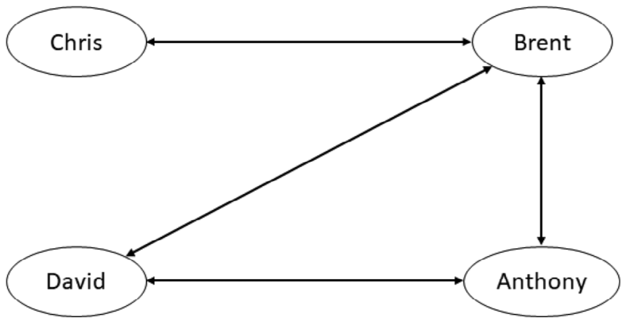


FIGURE 1 | Visual representation of the vignette used in Study 1. Text presented in the vignette: **"Anthony** offers help and advice to **Brent**. **Anthony** offers help and advice to **David**. **Chris** offers help and advice to **Brent**. **Brent** offers help and advice to **Anthony**. **David** offers help and advice to **Brent**. **David** offers help and advice to **Anthony**. **Brent** offers help and advice to **David**. Brent offers help and advice to **Chris**."

accuracy are contingent upon the structure of the network being recalled.

4 | Study 1

4.1 | Method

4.1.1 | Sample and Procedures

Our data for this study were derived from a larger project examining people's perceptions of the COVID-19 outbreak in the United States in 2020 (i.e., the COVID States Project; https://covidstates.org) via online surveys. Our sample comprised 10,304 respondents, of which 9614 provided complete responses, with 6533 (68%) of those being from women. Respondents' average age was 48.19 years (SD = 16.55), and they had an average of 14.48 years of education (SD = 2.39). The mean income of the survey population was $66,660 USD (SD = 52.09). Survey results were weighted to balance on age, gender, race/ethnicity, education, region, and rural/urban area of residence, based on US Census data, to make the sample representative of the US population.[3]

To measure participants' network recall accuracy, we adapted the procedure developed by Brashears (2013). Participants were first presented with a vignette portraying a network of four people with four undirected relationships (see Figure 1 for a visual representation of the vignette). They were asked to imagine that they were starting a new job and told that the vignette described their new coworkers and the advice relations between them. We gave participants 90 s to study the vignette. Then, following two short distractor questions, we asked participants to recall the network presented in the vignette. In the recall task, we displayed all possible relationships for each individual mentioned in the vignette in a random order and asked participants to select the relationships they remembered.

4.1.2 | Measures

4.1.2.1 | Network Recall Accuracy. We calculated network recall accuracy by multiplying participants' precision (i.e., correctly recalled ties divided by all recalled ties) by participants' coverage (i.e., correctly recalled ties divided by all depicted ties; Brashears 2013). This measure equals 1 when the participant recalled all the ties depicted in the vignette, and only those ties, and is less than 1 when the respondent recalled less than the total number of ties or recalled ties that were not depicted. Please see the robustness check section for replication of our results using different measurements of network recall accuracy.

Our measure focuses on the recall of ties because a network at a basic level is a set of persons (nodes or vertices) connected by a finite number of relationships (ties or edges). These ties are commonly treated as either present or absent. Network structure (e.g., triads, connected components, etc.) is an emergent result of the presence or absence of ties connecting a particular set of nodes. Thus, the ability of humans to remember structure is conditioned on their ability to recall the ties that comprise that structure. Recall of structural properties independent of ties that give rise to them (e.g., knowing a network is dense without recalling anything about who is connected to whom) is a manifestation of recall via heuristics, but is a very coarse type of recall that is unlikely to manifest as organizational advantage. Additionally, assessing the accuracy of such recall is problematic (e.g., how close to the true density must respondents recall the network as being in order to be correct?), and therefore we focus on the most fundamental, and unambiguous, aspect of recall accuracy: recall for ties.

4.1.2.2 | Control Variables. We included respondents' *age* as a control, given that previous studies have suggested that recall accuracy increases with age into adulthood (Lee, Foote et al. 2017). Additionally, since memory declines with increasing age, we also included a squared term to account for a potential non-linear effect. We also controlled for *income* in thousands of USD and *education* in years. Both variables have been identified in past research as affecting individuals' perception of networks (Iorio 2022; Smith et al. 2012; Soda et al. 2018). Moreover, in line with previous research (Brashears 2013; Brashears et al. 2016), we controlled for *overguess*, which we defined as the number of ties recalled by the participant divided by the total number of ties present in the vignette. When overguess equals 1, this indicates that the participant recalled exactly as many ties as were present in the network; when overguess is greater than 1, the participant recalled more ties than were present; and when overguess is lower than 1, the participant recalled fewer ties than were present. Controlling for overguess is important since participants who recall more relationships are, by default, more likely to identify relationships that actually exist or to misremember structural holes.

4.2 | Results

Descriptive statistics and correlations among study variables are presented in Table 1. As expected, gender was correlated with overall recall accuracy.

As shown in Table 2, we estimated an ordinary least squares (OLS) regression predicting participants' recall accuracy using gender as a main predictor and age (and age squared), education, income, and overguess as controls to test our baseline hypothesis.

TABLE 1 | Study 1: Descriptive statistics and correlations for study variables.

Variable	*M*	SD	1	2	3	4	5	6
1. Age	48.19	16.55						
2. Education	14.48	2.39	0.05***					
3. Income[a]	66.66	52.09	0.02*	0.45**				
4. Overguess	1.09	0.27	0.10**	−0.07**	−0.04**			
5. Women	0.68	0.47	−0.03**	−0.13**	−0.15**	0.04**		
6. Accuracy	0.80	0.13	−0.07**	0.06**	0.04**	0.25**	0.04**	
7. SH accuracy[b]	0.21	0.40	−0.12**	0.08**	0.07**	−0.34**	−0.02	0.58**

Note: N = 9614.
[a]Income in thousands of USD.
[b]SH: structural holes.
*$p < 0.05$;
**$p < 0.01$.

TABLE 2 | Study 1: Regression results predicting recall accuracy and structural holes recall accuracy.

	Ordinary least squares		**Logistic regression**	
	H1 Model 1	**H1 Controls Model 2**	**H2b Structural holes Model 3**	**H2b Structural holes controls Model 4**
Women	0.010***	0.011***	−0.098+	0.065
	(0.003)	(0.003)	(0.051)	(0.056)
Overguess		0.147***		−3.432***
		(0.005)		(0.122)
Age		−0.002***		−0.037***
		(0.0004)		(0.009)
Age squared		0.00002***		0.0002+
		(0.000)		(0.0001)
Education level		0.004***		0.074***
		(0.001)		(0.012)
Income		0.0001***		0.002***
		(0.00003)		(0.001)
Constant	−0.284	−0.557+	9.507+	−5.061
	(0.309)	(0.313)	(5.732)	(6.262)
Observations	9617	9614	9617	9614
Adj. *R*-squared	0.001	0.100		
Log likelihood			−4614.048	−3981.324
F-statistic	12.176*** (df = 1; 9615)	179.764*** (df = 6; 9607)		
AIC			9232.096	7976.648

+$p < 0.1$;
*$p < 0.05$;
**$p < 0.01$;
***$p < 0.001$.

The results (Table 2, Model 2) showed that women had higher accuracy than men (b = 0.011, SE = 0.003, $p < 0.001$) when recalling the overall social network, providing support for our baseline Hypothesis (H1) that women, compared to men, have more accurate recall of social networks.

In this study, we asked participants to recall only one network; hence, we cannot formally test our theory that women's network recall advantage is contingent upon network structure because we could not distinguish between less cohesive and more cohesive networks. However, the network depicted in the vignette contained two structural holes (between David and Chris and between Chris and Anthony, both centered on Brent, see Figure 1). Thus, although we cannot formally test Hypothesis 2 (and especially 2b), we can provide suggestive evidence by comparing women's and men's recall accuracy for the structural holes in the network depicted in the vignette as a proxy for their accuracy in recalling less cohesive networks. We assessed respondents' accuracy in recalling structural holes by measuring whether participants correctly identified the missing dyad characterizing a structural hole, conditional on correctly identifying the two existing relationships in each triad. The final variable is binary, equaling 1 when the respondent correctly identified at least one of the two structural holes, and 0 otherwise. Results of a logistic regression predicting participants' structural holes recall accuracy using the same predictors as in Model 2 (see Models 3 and 4 in Table 2) indicate that women lose their network recall advantage over men when accuracy is measured only in terms of structural holes (b = 0.065, SE = 0.056, p = 0.25), providing suggestive evidence in support of our theory that gender differences in network recall accuracy are contingent upon network structure.

4.3 | Discussion

The results of Study 1 confirmed Hypothesis 1. We found that women exhibit more accurate recall of social networks than men and that these results are generalizable to the US population. A limitation of this study is that it uses a hypothetical network to elicit network recall, which is not related to participants' real-life experiences. Accordingly, in Study 2, we tested Hypothesis 1 in a naturalistic environment involving participants' recall of their own network.

5 | Study 2

5.1 | Method

5.1.1 | Sample and Procedures

We obtained Cognitive Social Structure[4] (CSS) data from three cohorts of master-level students engaging in an elective course at a business school in the United Kingdom in 2013–2014.[5] Students were asked to report up to 10 individuals they considered friends. They were then asked to report the friendship ties among their friends and between their friends and the rest of the cohort. This procedure generated a matrix of perceived friendship networks for each respondent. Of the 171 students who took part in the course, 154 provided complete answers, for a response rate of 90%. The dataset included 113 men and 58 women.

5.1.2 | Measures

5.1.2.1 | Actual Friendship Ties. A challenge with CSS field data is the absence of a unique and common understanding of a network of actual relationships to be recalled, such as the network in Figure 1 used in Study 1. To address this, we followed prior literature on Cognitive Social Structures and constructed the actual network using a consensus-based approach (Krackhardt 1987).[6] In this approach, ties are considered to exist if a sufficient number of network members report their presence. While this method does not capture ground-truth behavioral interactions, it reflects shared perceptions of social reality, consistent with theories of cultural consensus and collective cognition (Batchelder and Anders 2012). In doing so, it provides a practically useful and socially meaningful representation of network structure, particularly when direct behavioral data are unavailable. Moreover, even if available, direct behavioral data are not necessarily reflective of social ties, given that not all interactions reflect relationships and not all relationships result in observable social interactions.

To compute actual friendship ties, we aggregated all matrices of perceived relationships within each cohort, resulting in an N*N matrix, where N is the number of students in the cohort and each cell is a count of the number of respondents who perceive the existence of a relationship between the actor in a row and the actor in a column. We then applied a threshold to this matrix to determine which relationships should be treated as "real." Selecting an appropriate threshold involves a meaningful tradeoff: lower thresholds (e.g., 0 or 1) may include ties that are idiosyncratic or misperceived, whereas higher thresholds require broader agreement but risk omitting real ties known only to a few individuals. We chose a threshold of three, reasoning that when at least three participants report a tie, there is sufficient consensus and visibility to justify treating it as part of the shared social structure.

This tradeoff parallels the familiar statistical balance type I and type II errors: lower thresholds risk false positives (mistakenly including ties), and higher thresholds risk false negatives (failing to include real ones). Figure 2 presents the number of relationships retained at each threshold level, illustrating how tie counts decline sharply as the threshold increases. For example, at a threshold of 6, 115 (out of 154) respondents would be left with no confirmed ties. To test the robustness of our findings, we created a set of binary matrices at thresholds from 2 to 5. Each matrix contains a 1 for a dyad if the tie was reported by more than the number of perceivers, and 0 otherwise.

5.1.2.2 | Network Recall Accuracy. We calculated network recall accuracy using the same approach as in Study 1. We considered the actual friendship network at each threshold value as a target network to be recalled and the network perceived by each participant as the network that they recalled.[7]

5.1.2.3 | Control Variables. We calculated each participant's *outdegree*, which is a count of the number of alters each participant nominated, as a measure of network size and visibility. We

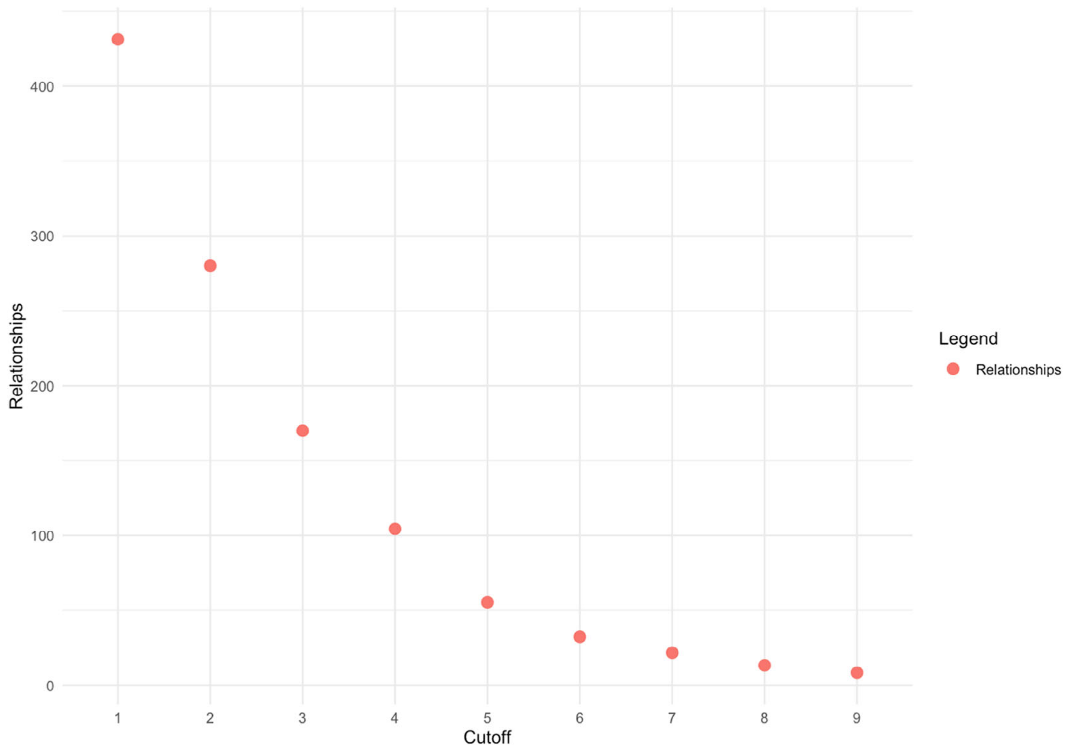


FIGURE 2 | Distribution of the number of relationships for each consensus threshold. A cutoff of 1 means that more than one respondent (i.e., two or more) agrees on the existence of the relationship.

TABLE 3 | Study 2: Descriptive statistics and correlations for study variables.

Variable	*N*	Mean	SD	1	2	3	4
1. Women	154	0.30	0.46				
2. Accuracy	144	0.08	0.11	0.04			
3. Outdegree	144	5.92	3.63	0.00	0.43**		
4. Overguess	144	0.23	0.26	0.00	0.52**	0.74**	
5. Density	144	0.34	0.30	−0.17*	0.52**	−0.13	0.06

Note: The final number of observations in the model is 144 because some individuals nominated only one outgoing friendship relationship.
*$p < 0.05$;
**$p < 0.01$.

also calculated ego network *density* to account for ego network shape, given that denser networks provide more opportunities for correct recall. Finally, our models include controls for the *cohort* each student belongs to and their original *program*, given that being in the same cohort or in the same program can meaningfully affect respondents' exposure to and ability to recall relationships.

5.2 | Results

Table 3 displays descriptive statistics and correlation coefficients between the variables included in the model, using a consensus threshold of 3: a tie was considered present if it was reported by three or more respondents. Table 4 presents the results of OLS regressions predicting respondents' network recall accuracy using Gender as our main predictor to test Hypothesis 1. The pattern of results presented in Table 4 shows that women have a significantly higher level of accuracy in identifying friendship relationships for thresholds ranging from 2 to 5 (see Models 1 to 4 in Table 4). This finding supports our hypothesis that women exhibit a higher recall accuracy than men. Our results were robust to the inclusion of additional controls, such as the Need for Closure, Relational Interdependence, and constraint (as a measure of structural position), as well as using alternative measurements of accuracy (see Robustness checks).

5.3 | Discussion

In this study, we tested Hypothesis 1 in a natural setting using a non-experimental approach. Our analysis revealed gender differences in recall accuracy in a sample of master students, supporting our hypothesis. This study provides evidence of the generalizability of our findings to real-world contexts. However, testing H2, which predicts that the relationship between gender

TABLE 4 | Study 2: Regression results predicting recall accuracy across thresholds from 2 to 5.

	Model 1	Model 2	Model 3	Model 4
Threshold	**2**	**3**	**4**	**5**
Women	0.030*	0.045**	0.048**	0.053**
	(0.012)	(0.016)	(0.017)	(0.019)
Outdegree	0.013***	0.016***	0.019***	0.019***
	(0.003)	(0.003)	(0.003)	(0.003)
Overguess	0.314***	0.104*	0.009	−0.013
	(0.057)	(0.044)	(0.027)	(0.011)
Density	0.221***	0.314***	0.473***	0.703***
	(0.021)	(0.029)	(0.037)	(0.050)
Constant	0.085	0.140*	0.126+	0.051
	(0.058)	(0.070)	(0.076)	(0.083)
Cohort	Yes	Yes	Yes	Yes
Program	Yes	Yes	Yes	Yes
Observations	144	144	144	144
Adj. R-squared	0.824	0.774	0.777	0.776
F-statistic (df = 18; 125)	38.068***	28.176***	28.738***	28.471***

Note: A threshold of 2 means that a friendship relationship between two people exists if more than two people reported it.
$^{+}p < 0.10$;
$^{*}p < 0.05$;
$^{**}p < 0.01$;
$^{***}p < 0.001$.

and network recall accuracy is moderated by the structure of the network, is not possible in this Study. Participants' networks are not experimentally induced but are instead the result of natural processes that sort men and women into particular locations. Given the varied and unobserved opportunities to practice schemas appropriate for those particular networks, as well as the likelihood that individuals will tend to sort themselves into network positions that they can cognitively manage, this hypothesis is not testable in these data. Therefore, in Study 3, we devised an experimental protocol enabling us to randomly assign women and men to recall either a more cohesive network or a less cohesive network. This experimental protocol enables us to examine the structural mechanism that we theorize underlies gender differences in network recall accuracy.

6 | Study 3

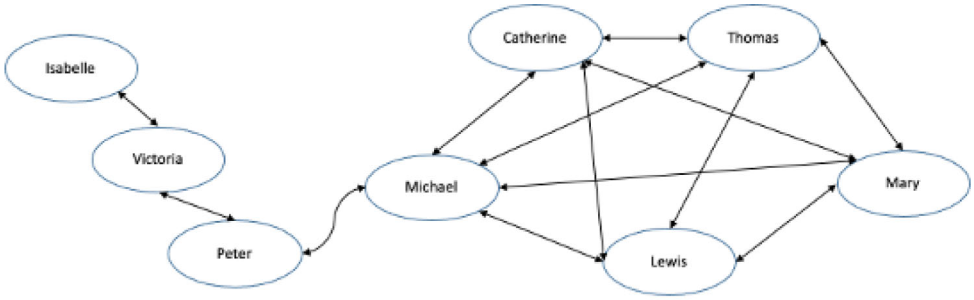
6.1 | Method

6.1.1 | Sample and Procedures

For Study 3, we pre-registered our study at AsPredicted.org (registration # 94910: https://aspredicted.org/sbhg-zhdh.pdf). The study received IRB approval from NEOMA Business School (#408326). We recruited an online sample of working adults from the United States with Prolific in 2022; 663 participants were invited to participate, out of which 625 provided complete responses. Participants were compensated 3.25 euros for completing the survey. The sample size was calculated using G*power 3 (Faul et al. 2009) to detect a medium-sized effect (f = 0.20; consistent with Brashears and Quintane 2015) with a power of 0.95 and two groups. We first asked participants to report their gender and then presented them with a vignette portraying eight individuals and their relationships (13 undirected relationships). We created two versions of this vignette, adapted from Brashears (2013), representing two distinct experimental conditions: a more cohesive network (with fewer structural holes) and a less cohesive network (with more structural holes). A full description of the vignette is presented in Figure 3. There were no closed triads in the condition with more structural holes (15 potential structural holes). By contrast, there were six structural holes in the condition with fewer structural holes. Ideally, we would have included a condition with no structural holes at all; however, achieving this would have required us to change either the number of actors or the number of relationships in the networks. To keep the number of relationships and actors constant across conditions, we therefore could not include a no-structural-holes condition, as changing these variables would have altered the total amount of information participants needed to recall—a result we aimed to avoid. Despite this, our configuration allowed for the maximum possible difference in structural holes between conditions, ensuring we could effectively test our hypotheses.

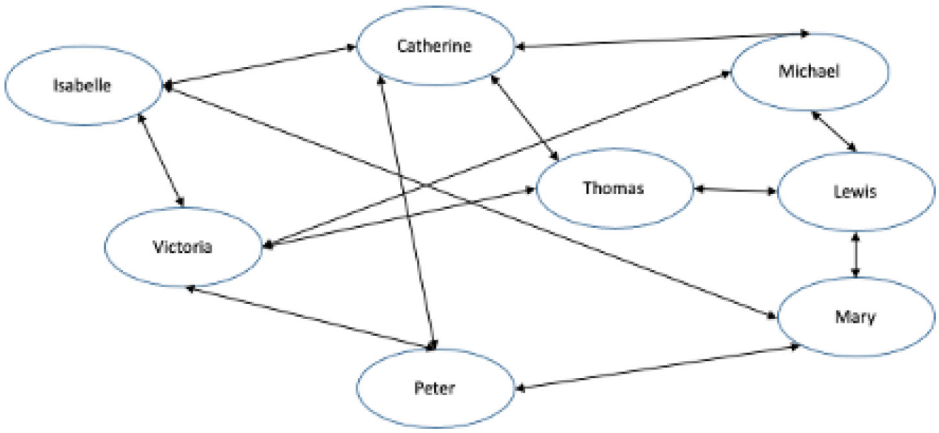
We assigned participants randomly to one of the two conditions, ensuring that differences between conditions could not be attributed to unobserved variables, and thus, we adopted a between-subjects design. Next, we asked participants to complete a masculinity/femininity scale (Kachel et al. 2016), which was

A. More Cohesive Network (8 actors, 13 relationships, 6 structural holes)



"Catherine, who graduated from Princeton, co-leads a team with Thomas, who matriculated from Northwestern. Peter, an avid handball player, is Catherine's geneticist. Michael is Catherine's chemist. Thomas is the supervisor of Lewis, who listens to classical music, as well as Michael and Mary. Mary, who takes medicine for breathing problems, prepares research samples for Catherine. Lewis is the former student of Catherine. Michael and Lewis work together in the same laboratory. Victoria is assisting Peter with experiments. Isabelle shares an office with Victoria. Peter likes to have lunch with Michael."

B. Less Cohesive Network (8 actors, 13 relationships, 15 structural holes, no triads)



"Catherine, who graduated from Princeton, co-leads a team with Thomas, who matriculated from Northwestern. Peter, an avid handball player, is Catherine's geneticist. Michael is Catherine's chemist. Thomas is the supervisor of Lewis, who listens to classical music. Thomas also works with Victoria. Mary, who takes medicine for breathing problems, prepares research samples for Lewis. Lewis and Michael work together in the same laboratory. Victoria is assisting Peter with experiments. Isabelle shares an office with Victoria. Isabelle also provides online assistance to Catherine. Mary and Isabelle like to have lunch together. Mary often plays tennis with Peter. Michael and Victoria ride their bike together to the office."

FIGURE 3 | Visual representation of the vignettes used in Study 3.

also used as a distractor task, and then to recall the depicted network in the same way as in Study 1. Finally, participants answered additional questions about their demographics.

After removing those participants who spent less than 2 min completing the survey (18), failed attention checks (58), acknowledged that they took notes during the recall task (33), or did not identify as man or woman (9), our final sample consisted of 507 participants. The average age was 36.15 years (SD = 12.72), with 252 women (49.70%). Of the total sample, 66.27% had at least a 2-year professional degree, and 56.61% had an income of $60,000 USD or higher.

6.1.2 | Measures

6.1.2.1 | Network Recall Accuracy. We measured network recall accuracy in both conditions using the same metrics as in Studies 1 and 2. However, recall accuracy did not follow a normal distribution. Therefore, we used a square root transformation to recover the normal distribution. We conducted robustness checks using the original variable, and our results were substantively identical.

6.1.2.2 | Masculinity/Femininity. Since gender can be considered as a spectrum rather than a binary identity (Brands

TABLE 5 | Study 3: Descriptive statistics and correlations for study variables.

Variable	*M*	SD	1	2	3	4	5	6	7
1. Age	36.15	12.68							
2. Education[a]	4.39	1.42	0.18**						
3. Income[a]	7.14	3.35	0.12**	0.31**					
4. Overguess	0.62	0.29	−0.07	−0.07	−0.07				
5. Women	0.50	0.50	−0.11*	−0.01	0.00	0.11*			
6. Accuracy	0.28	0.20	−0.02	0.02	0.06	0.48**	0.05		
7. Femininity	23.41	10.10	−0.08+	0.00	0.01	0.14**	0.85**	0.09*	
8. Network condition[b]	0.50	0.50	−0.02	−0.08	−0.05	−0.02	0.01	−0.00	−0.03

Note: $N = 507$ ($N = 499$ for femininity).

[a]Education and Income (in tens of thousands of USD) were recoded as continuous variables to provide descriptive statistics.

[b]More cohesive = 1.

*$p < 0.05$;

**$p < 0.01$.

et al. 2022; Hyde et al. 2019), we asked participants to complete a femininity/masculinity scale (Kachel et al. 2016, $\alpha = 0.96$) to obtain a more granular assessment of the degree of gender identification. This measure comprised six items on a Likert scale ranging from 1 (*very masculine*) to 7 (*very feminine*). An example item is: "I consider myself as…"

6.1.2.3 | Control Variables. We measured participants' age (in years), education level, and income. Education level was measured by capturing relevant education levels in the United States from 1 (*less than a high school degree*) to 7 (*doctoral degree*). Income was measured as a categorical variable, with participants selecting one of 12 salary ranges (e.g., "less than $10,000," "$10,000 to $19,999," up to "more than $150,000").[8] We use these control variables in robustness checks.

6.2 | Results

Table 5 contains descriptive statistics and correlations among study variables. In this sample, gender was not significantly correlated with accuracy (but femininity was), but gender and femininity were highly correlated.

Hypothesis 2 predicted that the effect of gender on network recall accuracy is contingent upon network structure. We estimated a linear regression[9] (Table 6, Model 1) predicting recall accuracy using the interaction between gender and network condition as a predictor, controlling for overguess. The positive and significant parameter estimate of the interaction term ($b = 0.068$, SE = 0.029, $p = 0.027$) confirmed that network structure moderates the relationship between gender and network recall accuracy.

Hypotheses 2a and 2b make more specific predictions regarding how network structure moderates the relationship between gender and network recall accuracy. Hypothesis 2a predicted that women would recall more cohesive networks more accurately than less cohesive networks, whereas men would recall more cohesive networks as accurately as less cohesive networks. We estimated a linear regression (Table 6, Model 2) predicting recall accuracy of women using network condition as a predictor, controlling for overguess. The positive and significant parameter estimate ($b = 0.045$, SE = 0.020, $p = 0.027$) confirmed that women had more accurate recall of more cohesive networks than less cohesive networks. In contrast, the same analysis for men (Table 6, Model 3) showed that the parameter estimate for men was not significant ($b = -0.022$, SE = 0.021, $p = 0.299$) confirming our prediction that the recall accuracy of men is not affected by this variation in network structure. Thus, Hypothesis 2a was supported.

Hypothesis 2b predicted that women would recall more cohesive networks more accurately than men, but there would be no gender difference between men and women in the recall of less cohesive networks. To test our hypothesis, we estimated a linear regression predicting network recall accuracy in the more cohesive network condition, using participants' gender as a main predictor and controlling for overguess. The results of the regression (Table 6, Model 4) showed that women were significantly more accurate than men in the more cohesive network condition ($b = 0.042$, SE = 0.019, $p = 0.030$). Model 5 in Table 6 shows that the parameter estimate for women in less cohesive networks is not significant ($b = -0.034$, SE = 0.021, $p = 0.119$), confirming that the recall accuracy of men and women is indistinguishable in the less cohesive network condition. Thus, Hypothesis 2b was supported.

Our results were robust to including age, income, and education as controls to mirror the models presented for Study 1. Moreover, our results remained substantively similar when using femininity instead of gender as a predictor of network accuracy (see Robustness Checks). Respondents high in femininity exhibited superior recall in the *more cohesive network* condition, but this recall advantage disappeared in the *less cohesive network* condition.

6.3 | Discussion

Study 3's results provided evidence for our theory that women's network recall advantage is contingent upon the structure of the network to be recalled. We find that women are more

TABLE 6 | Study 3: Regression results predicting recall accuracy.

	H2	H2a		H2b	
		Women	Men	More cohesive network	Less cohesive network
	Model 1	Model 2	Model 3	Model 4	Model 5
Women	−0.029			0.042*	−0.034
	(0.020)			(0.019)	(0.021)
Network condition	−0.023	0.045*	−0.022		
	(0.020)	(0.020)	(0.021)		
Overguess	0.318***	0.266***	0.384***	0.262***	0.397***
	(0.025)	(0.033)	(0.038)	(0.031)	(0.041)
Women * Network condition	0.068*				
	(0.029)				
Constant	0.310***	0.315***	0.270***	0.320***	0.262***
	(0.021)	(0.026)	(0.027)	(0.022)	(0.029)
Observations	507	252	255	251	256
Adj. *R*-squared	0.248	0.215	0.284	0.244	0.268
F-statistic	42.637***				
(df = 4; 502)	35.401***				
(df = 2; 249)	51.282***				
(df = 2; 252)	41.348***				
(df = 2; 248)	47.799***				
(df = 2; 253)					

Note: Model 2 predicts women's network recall accuracy using Network Condition as the main predictor. Model 3 predicts men's network recall accuracy using Network Condition as the main predictor. Model 4 predicts participants' network recall accuracy in the more cohesive network condition using Gender as the main predictor. Model 5 predicts participants' network recall accuracy in the less cohesive network condition using Gender as the main predictor.
$^{+}p < 0.10$;
$^{*}p < 0.05$;
$^{**}p < 0.01$;
$^{***}p < 0.001$.

accurate than men in recalling more cohesive networks, but this recall advantage is diluted in less cohesive networks, which are characterized by many structural holes. As predicted, we also find that men's network recall is not affected by the structure of the network, consistent with a less pronounced use of the closure schema.

7 | Robustness Checks

We conducted a series of robustness checks to ensure that the validity of our results was not affected by idiosyncratic decisions we made. Details about the robustness checks are reported in the appendices. The following is a summary of the checks and results.

First, we performed additional analyses intended to test the robustness of our findings to different measurements of our dependent variable. We measured network recall accuracy in seven different ways, and our results were robust and largely supported by the different measurements of our outcome variable. More specifically, building on Krackhardt (1990) and Gower and Legendre (1986), we selected five measures of similarity between two pairs of binary networks (Pearson, Jaccard, Dice, Ochiai, and Czekanowski). These measures assessed the similarity between the network depicted in the vignette (Studies 1 and 3) or the consensus network (Study 2) and the network recalled by each participant in slightly different ways. We also implemented a Bayesian approach to assessing the dissimilarity between networks (Butts 2003). Furthermore, given the warning by Certo et al. (2020) regarding the use of ratios in the measurement of variables in management research, we replicated our analyses using the number of correctly identified relationships as the dependent variable while controlling for the total number of relationships, instead of overguess. The full tables containing all robustness checks with the different operationalizations of the dependent variables are available in the appendices. For Study 1 (Table A1), our result that women have more accurate recall of social networks was replicated in all but one case (Bayesian Accuracy). Our results are fully replicated for Studies 2 and 3 (Tables B1 and C1). Therefore, our finding that women have a recall accuracy advantage in more cohesive networks, which is lost in less cohesive networks, is not an artifact of any specific approach to measuring accuracy, confirming our hypotheses about the nuances explaining gender differences in network recall based on cognitive schemas.

Second, we conducted additional robustness checks for Studies 1 and 3. We replicated our main models, presented in Table 2, without rebalancing the sample using the weights to make the population representative of the US population (See Table A2). As robustness checks of the results presented in Study 3, we estimated the models testing Hypotheses 2a and 2b using femininity instead of gender (See Table C2). We also estimated the models presented in Study 3 using the same controls as those included in Study 1, as well as using categorical variables for income and education level (see Tables C3 and C4). Our results for Study 3 remained substantively unchanged. Finally, in Study 3, our experimental design enabled us to provide a robust test of the impact of the number of structural holes on the network recall accuracy of men versus women. In a robustness check, we followed the procedure outlined by Lee, Lease et al. (2022) using Butts' (2003) Bayesian approach to confirm between false positives (incorrectly identified existing ties) and false negatives (incorrectly identified missing ties). We did not attempt to replicate the analysis for Study 1 because our analysis of structural holes is already an analysis of false positives. Supporting our theory, the results presented in Table C5 showed that women made significantly more false positive errors in the less cohesive network condition relative to the more cohesive network condition. However, women's propensity to make false negative errors in the less cohesive condition was indistinguishable from their propensity to make false negative errors in the more cohesive condition. Men's propensity to make positive or negative errors was unaffected by network structure.[10] Thus, this additional test provides compelling evidence for women's reliance on the closure schema in network recall.

8 | General Discussion

In this research, we examine gender differences in social network recall accuracy. We make multiple contributions to the existing literature on gender and network perceptions. First, we provide robust evidence that women have, on average, more accurate recall of social networks than men. While experimental studies have hinted at this difference (Brashears et al. 2016; Lampronti et al. 2025), our results establish its generalizability in two important ways. In Study 1, we replicate the finding in a large, demographically representative sample of the US population using the same vignette-based method common in experimental work. In Study 2, we extend the results to a naturalistic context by showing that women recall their actual social environments more accurately than men. These findings lend strong support to the empirical regularity of women's recall advantage and expand its scope beyond controlled experimental settings. Importantly, this observed gender difference reflects not only individual variation but also the structural characteristics of many real-world networks. Because social networks often exhibit substantial closure, individuals who more strongly rely on closure-based mental schemas, such as women, due to gendered patterns of socialization, are more likely to benefit in terms of recall accuracy. In this sense, the average advantage observed for women is consistent with both the cognitive mechanisms we propose and the structural realities of the environments in which recall occurs.

Second, our central theoretical contribution lies in showing that gender differences in recall accuracy are contingent on network structure. Specifically, we propose that differences in socialization lead women to develop and rely more on the closure schema—a mental shortcut that assumes connections between individuals who share a common contact. Because this schema is well-suited to cohesive networks but less so to networks with structural holes, women's recall advantage emerges primarily in cohesive networks and disappears in sparser ones. We demonstrate this contingent pattern in Study 3 using an experimental design with randomly assigned network structures, finding that women outperform men only when the structure of the network aligns with their schema. This contingent perspective helps clarify why previous organizational studies often failed to detect a gender effect in network accuracy: many examined brokerage or sparse networks where the closure schema is less applicable. By identifying the conditions under which gender differences emerge, our work reconciles prior inconsistencies in the empirical literature and sharpens the scope of gender-based differences in network cognition.

Our work also contributes to research on gender and social networks by offering a novel cognitive explanation for women's underrepresentation in brokerage roles. Prior research has shown that women tend to occupy less structurally advantageous network positions in organizations (e.g., Ibarra 1992; Ibarra and Andrews 1993). A recent meta-analysis confirms that compared to men, women are less likely to build and inhabit sparse, less cohesive networks (Fang et al. 2021). This is a key source of gender disadvantage in organizations because such broker networks are associated with significant creativity, performance, and career benefits (see Kwon et al. 2020 for a recent review). Prior literature has focused on the potential for sparse, less cohesive networks to be male-typed, leading to stereotype-derived penalties for women whose networks are characterized by openness, as well as feelings of threat in the women themselves (Brands and Kilduff 2014; Brands and Mehra 2019). We complement these accounts by proposing a cognitive pathway: women may be less likely to notice structural holes in their surrounding networks, due to lower recall accuracy in sparser settings. This, in turn, may make it harder for them to recognize or capitalize on brokerage opportunities, even when structurally available.

More broadly, our findings show that recall accuracy is not evenly distributed across individuals or network contexts. We argue—and find empirical support—that women's greater use of the closure schema, rooted in patterned exposure to cohesive networks, enhances their recall in settings characterized by closed triads but provides less benefit in sparse networks. This theory enables us to explain both when gender differences in network recall are likely to emerge and why they take the form they do.

These insights open several promising avenues for research because they show that the use of the closure schema can vary across individuals, which has not been considered in previous research. While we focused on participants' gender, it is possible that other individual- or group-level characteristics associated with individuals' experience of socialization could also affect their use of the closure schema (e.g., cultural values). In addition, our results cast doubt on the ability of individuals to flexibly adjust their mental schemas based on the underlying structure of the social network that they observe (see Brashears and Quintane 2015). Instead, our findings suggest that mental schemas seem to be applied rather indiscriminately, which leads to predictable and systematic errors in recall once the network to be recalled deviates from the established mental schema. For example, men's broader exposure to structurally diverse networks may not only reduce the consolidation of specific schemas but also introduce ambiguity in which schema to apply in a given context. While we did not measure cognitive processing time, future research might examine whether such ambiguity affects not only recall accuracy but also the speed of recall decisions. Finally, while individuals might be flexible in the application of mental schema, our results suggest that this flexibility may be limited, raising questions about the development of mental schemas, the potential for these schemas to change, and for new schemas to be learned once some schemas are well-established. For instance, groups that adopt more hierarchical structures than are typical (e.g., the military, cults) often exhibit a highly intense training period for new members (e.g., "boot camp"), which may suggest that the level of effort needed to override established schema is quite high.

9 | Limitations

Despite using multiple methods and samples to investigate network recall differences between women and men, our work remains limited in several ways. Most simply, our use of online surveys and experiments reduced our level of control over respondent conditions relative to a laboratory study and likely introduced more noise. Indeed, we identified smaller effect magnitudes than in prior work; for example, being a woman (vs. a man) increased network recall accuracy by 0.011 in Study 1 (Table 2, Model 2) and by 0.042 in Study 3 (Table 6, Model 4), which is noticeably smaller than the effect reported in Brashears et al. (2016).[11] However, this limitation is also a strength in that our use of online surveys and experiments allowed us to assess these effects with a much larger and more diverse population than is typically available for laboratory experiments. Moreover, our survey experimental design forced us to present much simpler vignettes to the participants (only four actors[12] and four relationships in Study 1, and eight actors with 13 relationships in Study 3) than those used in Brashears and colleagues' earlier work. This change made the recall exercise far less taxing, which helped compensate for the increased distractions outside of the lab, but also constrained the opportunities for subjects to provide correct or incorrect answers. As such, our measures may have underestimated the size of the effects.

Additionally, our data do not allow us to examine additional network characteristics that may affect gender differences in network recall. For instance, the type of ties within a network, such as friendships versus leadership connections, could shape how men and women recall these ties. Women's communal orientation may lead them to perceive all ties similarly in an organizational context, potentially applying closure schemas regardless of the tie type. In contrast, men's agentic approach might make them more attuned to differences in tie types, which could enhance their recall accuracy. Future research could explore how this and other network features influence gender differences in network recall.

A further limitation of our approach lies in the construction of the actual network in Study 2. Because we relied on perceptual consensus rather than observed behavior, the resulting network captures socially shared beliefs rather than verified interactions. This aligns with work on cognitive and cultural consensus (Batchelder and Anders 2012; Krackhardt 1987), but it also raises epistemological concerns: agreement among perceivers may reflect social visibility or normative expectations, rather than relational fact (Lee and Butts 2018, 2020). At the same time, behavioral data are not necessarily a definitive benchmark: frequent interactions may be less socially central than less observable but more meaningful ties. In this sense, perceptual consensus may capture a distinct but valid form of relational truth—particularly regarding cognitively or emotionally salient ties. Classic work suggests that recall emphasizes regularities over episodic details (Freeman et al. 1987); by aggregating across perceivers, consensus methods extend this logic to highlight patterns that are not only cognitively salient but also socially visible and shared. Future research should combine consensus-based and behavioral approaches to more precisely evaluate tie existence and recall accuracy.

Our work also shares a limitation with previous studies that have explored network-based mental schemas since we are not able to measure the mental schema itself but only observe systematic departures from an expected result as evidence for the mental schema. However, the fact that we could replicate the same result in three different studies using different approaches provides support for our postulated mechanism. Finally, our empirical study is limited to the extent that there are multiple confounding factors that affect both the recall of networks and the opportunities to observe and recall these networks. The combination of experimental study, online survey, and field study nevertheless provide support for our findings. We hope that future research will replicate these results in different settings to better understand the scope conditions of the validity of these results.

10 | Practical Implications

In addition to benefiting the literature on gender and network recall, our results have notable implications for practice. Individual performance at various tasks has long been attributed not simply to individuals' capabilities (i.e., human capital) but to the structure of the relationships in which these individuals are embedded (i.e., social capital). While these embeddings are not entirely an individual product, it is nonetheless evident that agentic behavior is (at least somewhat) capable of influencing network structure. However, individuals can only manipulate network structures that they can perceive and understand, which also means they are liable to make suboptimal changes to networks whose structure they misapprehend. Therefore, the quality of network perception and recall is a key element in individual achievement. Many business objectives are served by enhancing relationships between individuals and organizations (e.g., Granovetter 1985; Uzzi 1996), and a correspondingly large amount of effort is expended on products (e.g., LinkedIn) and practices (e.g., the "Farley file"[13]) intended to achieve such ends. Hence, improved understanding of how humans mentally encode and recall social information will support the development of more effective business aids.

Practically, our results indicate that greater care should be exercised in designing interventions meant to address longstanding inequities between men and women in the workplace. While networking events and training are well-intentioned, they will have minimal effects if they are structured as if men and women approach networks with identical preconceptions and tendencies to employ specific heuristics. Our work suggests that interventions should be tailored to the recipient, training men in managing more cohesive networks and women in managing less cohesive networks. Moreover, the suggestion that gender-based differences in network recall are rooted in socialization rather than biology means that this tailoring will require ongoing tweaking. Changes in the distribution of men and women across roles in business and society will alter their default mental schemas and, by extension, the biases and shortcomings they bring to the workplace. This variability presents some difficulty, in that training will need regular revision to maintain relevance; yet it is still preferable to a world in which training becomes ineffective and pointless.

Finally, managers should consider that disparities in the perception of their immediate network between men and women are significantly shaped by socialization processes. As a result, implementing strategies that enhance awareness of group dynamics can contribute to employees gaining a more comprehensive grasp of their overall network. Concurrently, managers ought to direct the focus of women toward potential brokerage opportunities that might otherwise elude them, though this will be enhanced by the training we describe above. This approach could yield significant behavioral outcomes, given that recognizing one's standing within a network, especially in terms of brokerage positioning, constitutes a wellspring of structural advantage (Burt 1992).

11 | Conclusion

Our studies consistently show a difference in overall network recall accuracy between men and women, with women exhibiting superior performance across multiple samples. Further, we theorize that women's network recall advantage comes from a more pronounced use of a triadic closure mental schema by women. Our results support this theory by showing that while women are more accurate overall and in more cohesive networks, they show no advantage over men when networks are less cohesive and characterized by structural holes. Our results provide directions for future research and show the promise of continuing research into how humans encode, represent, and recall social information.

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Endnotes

[1] Studies have also shown that these mental schemas apply to social relationships but not to associations between objects that are not social in nature (see, e.g., Mason et al. 2010; Simpson et al. 2011)

[2] Societal expectations about the role women play as kin keepers have remained remarkably constant over the last 40 years (Braithwaite et al. 2017).

[3] Please see the following article from the COVID States project for additional information regarding the sample (https://osf.io/qxez5). We replicated the models presented in Table 2 and confirmed that our results were robust when the sample was not rebalanced using weights representative of the US population.

[4] Cognitive Social Structure refers to participants' cognitive representation of the social structure of a social network, usually to which they belong (see, Brands 2013; Krackhardt 1987).

[5] This dataset was originally presented as Study 2 in an article published in the Academy of Management Journal in 2019 ("Gender, Brokerage, and Performance: A Construal Approach" by Raina A. Brands and Ajay Mehra). This manuscript examines a different research question than the original article and is in no way a critique, correction, or commentary of the original publication.

[6] Krackhardt (1987) identified three methods of aggregation of CSS (Slice, Locally aggregated, and Consensus Structures). The Slice method is not applicable to our context. While the Locally Aggregated approach is applicable, it is less suitable in our context because relations need to be observable outside of the ego-alter dyad.

[7] To calculate the measures of network recall accuracy, we removed ego from the perceived network when comparing it to the actual friendship network. We believe this approach is more adequate in our context because the recall of direct relationships between each ego and their alters provides less meaningful information about their recall. Our results are replicated when including ego in the calculation of recall accuracy.

[8] To match the variable used in Study 1, we converted the categories into continuous variables. For education, we imputed the number of years of study based on the education level standards in the United States. For income, we imputed the lower bound salary in the range of thousands of USD. We conducted robustness checks using both continuous and the original categorical variables, and our results were substantively similar to those presented here.

[9] We use linear regressions (OLS) to parallel our analysis in Study 1. The results of MANCOVA are identical to those presented here.

[10] We thank an anonymous reviewer for suggesting this analysis. Note that in our experimental design, the less cohesive network condition has only very few missing ties that do not close a structural hole. Hence, the existence of false positives in the less cohesive network condition is highly related to the inaccurate recall of structural holes as closed.

[11] We are unable to make a similar comparison with the results presented by Lee, Foote et al. (2017) or Lee, Lease et al. (2022) because of research design differences.

[12] Note that the four actors in the vignette we used for Study 1 are all men, which arguably represents a conservative test of women's recall accuracy, given that women may be more attuned to the existence of relationships among other women. We leave this line of questioning open for further research.

[13] The Farley file is a personal archive of social details (e.g., past conversations, preferences, names) used to manage impressions.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.

Supporting Table A1. Replication of the main result of Study 1 using different measurements of accuracy. **Supporting Table A2**. Replication of main models of Study 1 without rebalancing the sample using weights. **Supporting Table B1**. Replication of the main result of Study 2 using different measurements of accuracy. **Supporting Table C1**. Replication of the main result of Study 3 using different measurements of accuracy. **Supporting Table C2**. Study 3. Replication of the Main Models Using Femininity instead of Gender as a predictor. **Supporting Table C3**. Study 3. Replicating the Main Models with the Same Controls as in Study 1. **Supporting Table C4**. Study 3. Replicating the Main Models with the Same Controls as in Study 1, with categorical controls for education and income. **Supporting Table C5**. Study 3. Analysis of within gender effects of false positive and false negatives.