CANADIAN PSYCHOLOGICAL ASSOCIATION SOCIÉTÉ CANADIENNE DE PSYCHOLOGIE

Canadian Journal of Experimental Psychology /
Revue canadienne de psychologie expérimentale

ISSN: 1196-1961

https://doi.org/10.1037/cep0000353

Collective Memory and Fluency Tasks: Leveraging Network Analysis for a Richer Understanding of Collective Cognition

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Collective memory broadly refers to the memories shared by a group of people. Interest in collective memory among cognitive psychologists has boomed in recent years, with many studies leveraging fluency tasks to probe what events and people come to mind given a prompt. As other research using fluency tasks has benefitted greatly from network analysis (e.g., semantic memory research), it seems there is an opportunity to deepen our understanding of collective cognition and changes in collective cognition by adopting a network perspective. In the current article, we ask whether collective memory investigations could be enriched by harnessing the tools of network science. We start by reviewing the relevant collective memory literature and touch on the deep semantic memory literature to the extent it provides ties to network analysis for present goals. Our novel contributions to the topic include the introduction of a large fluency data set collected over the course of a decade as part of a task embedded within several research projects. We conduct several descriptive analyses and initial, proof-of-concept network analyses examining collective memory for U.S. cities. Some cities—those that are recalled most frequently—are recalled at similar rates and in similar output positions across time and task contexts. Our network approach suggests that recall transitions (e.g., recalling *Los Angeles* and *San Francisco* in adjacent positions) are made at similar rates as well. Together, these complementary approaches suggest a striking stability in both what people recall and their ordering, providing a window into the composition of collective memories.

Public Significance Statement

Large groups often converge on a shared representation of the past known as collective memory. When asked to generate U.S. cities in studies conducted across a decade (2011–2021), students ($N = 625$) in the Northeast United States report similar cities in similar orders, grouping them in common ways. By leveraging network analysis to characterise memory search in this context, we map not only shared knowledge but also the patterns that underlie how a collective navigates memory—something that may be critical for understanding how groups converge on shared stories and narratives.

Keywords: collective memory, network analysis, fluency task, recall, U.S. cities

Q20 *Supplemental materials:* https://doi.org/10.1037/cep0000353.supp

Memory researchers have long endeavoured to understand how people recall the past (e.g., Ebbinghaus, 1885; Schacter, 2002). While it is true that in the lab and in day-to-day life, memory is frequently relied on by people working in relative isolation (e.g., remembering to take daily medication, reminiscing past events), individual memory processes are not immune to social influence or the broader cultural context. Likewise, what a collection of people remembers has revealed patterns not evident by focussing on

Debra Titone served as action editor.
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Q2 Parts of this work were presented at the 62nd Annual Meeting of the Psychonomic Society (2021; virtual) and the 14th Biennial Meeting of the Q3 Society for Applied Research on Memory and Cognition (2023; Nagoya, Japan). The data analysed in this article, along with code to reproduce analyses and visualisations, are available on the Open Science Framework (private view-only link for peer review at https://osf.io/k3x9y/?view_only=0bc8ea9 Q4 b24de45b692ab49c81b77da90). These materials will be made publicly available upon publication.

The authors declare no conflicts of interest. The preparation of this manuscript was supported by the National Science Foundation Graduate Research Fellowship 1839287 and the National Science Foundation Grant 1456928. This article was funded by the Google Faculty Research Award (Grant 2014_R2.255.1) awarded to Suparna Rajaram and the Stony Brook Psychology Endowed Award Fund—Cognitive Science awarded to Garrett D. Greeley. The authors thank Annesta Batuwangala Q5 and Melissa Chen for assistance with data transcription and Jacqueline Bohk and Rachel Truskinovsky for assistance with spell checking/response coding. The authors also thank Jasmine Mui, Matthew Miller, and Vanessa Chan for data processing assistance during earlier iterations of this project.
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individuals in isolation. That is, a focus on *collective memory* implies an interest in where memories intersect—the people, places, and events that exist in the memories of many (Halbwachs, 1980, 1992/1925). Tapping into what the collective converges on remembering, be it a small group or an entire nation, is a powerful way to understand how groups represent their collective knowledge and past experiences.

Cognitive–psychological interest in collective memory has
Q6 boomed in recent years (e.g., Barnier & Sutton, 2008; Hirst & Manier, 2008; Rajaram, 2022; Wertsch, 2008; Wertsch & Roediger, 2008). The psychological approach to studying collective cognition leverages different research approaches and different tasks to get at this question. In the present work, we focus on the approach that relies heavily on the use of fluency task variations (i.e., generating as many items as possible from a given category, such as events and names, within a specified time; e.g., Van Overschelde et al., 2004). Studies leveraging this approach have shed light on the information that has cultural staying power in memory; for example, events that are considered to be most essential to the founding of the United States among different American subgroups (e.g., Yamashiro et al., 2022). A valuable contribution from these studies is that they provide rich and complex data about how groups view the collective past.

Fluency tasks have a long history in cognitive psychology, especially in research on semantic memory. Drawing from this body of work, cutting-edge analytical tools available to characterise large data sets—most notably network analysis—could add a deeper understanding to collective memory but remain unexplored. With this connection in mind, two specific goals guide the present study. First, we aim to highlight the common threads between the collective memory literature and work on semantic memory that has
Q7 leveraged network analysis (part one: collective memory, semantic memory, and networks). As collective memory researchers seek a richer understanding of what and how groups of people represent their past, the quantitative tools often employed by those studying semantic memory could help provide further insight. Second, we introduce a large fluency data set compiled over the course of a decade, along with a number of proof-of-concept network analyses, to illustrate how a network perspective could enrich the study of
Q8 collective memory (part two: proof-of-concept collective memory networks). With this illustration, we provide a basic template that could be extended to other fluency data collected in the context of collective memory research. We hope to initiate a conversation about the value that network analysis can offer to collective memory researchers. Finally, we offer the strengths and limitations of the research we present in this article.

Part One: Collective Memory, Semantic Memory, and Networks Q9

Defining Collective Memory in Cognitive Psychological Research

Sociologists have long studied how shared memories mould a group's overall collective narrative and identity (Halbwachs, 1980, 1992/1925). That is, collective memory at a cultural level may provide a relatively stable reference from which members base claims about the group's status or identity (e.g., "*We are* the land of the free" or "*We are* better than this"; see Assmann & Czaplicka, 1995). More recently, cognitive psychologists have become interested in examining which memories are and are not collectively remembered across group members (e.g., Hirst et al., 2018; Rajaram & Pereira-Pasarin, 2010). That is, collective memory refers to the memories shared by individuals within a group. While this definition deviates from how collective memory was originally defined to the extent it may not refer to identity, it provides a straightforward operational definition for conducting cognitive psychological research and has guided growing research in psychology. Using this conceptualisation, two broad approaches have been employed to assess collective memory.

In one approach, cognitive psychologists have used experimental settings to assess how collective memory is formed through discussion. In experiments focused on investigating how collaboration and conversation promote the emergence of collective memory in small groups, information shown earlier that former collaborators converge on recalling (e.g., all members of a group recall the target word *dog*) is considered collectively remembered (e.g., H. Y. Choi et al., 2014; Rajaram et al., 2022). Here, the experimenter can also compute the studied information that no one reports, that is, collective forgetting (e.g., H. Y. Choi et al., 2014; Cuc et al., 2007). This methodological approach is flexible and affords significant experimental control such that researchers decide what materials are studied, how participants interact, and how many times they interact (e.g., H. Y. Choi et al., 2017; Congleton & Rajaram, 2014). Specifically, when the set of target material is discrete, there is a set maximum for what can be collectively remembered and collectively forgotten. Likewise, researchers are free to control how collaboration/discussion takes place (e.g., some studies pick one person to be the speaker, Cuc et al., 2007; other studies specify turn-taking among group members, Basden et al., 1997; yet other studies allow Q10
free-flowing conversations, Weldon & Bellinger, 1997).

In another approach, researchers typically ask people to report information relevant to their group's past. Here, if researchers are interested in how already existing groups remember their collective past (e.g., how Americans remember the founding of the United States), then they often will tap into these collective memories via surveys. This approach is more relevant to the current project. In this context, researchers usually look at the specific pieces of information that large portions of the respondents recall. For example, authors have highlighted "core events" that are recalled by 50% or more people of the overall sample (e.g., across all respondents from all countries) and/or 50% of a given sample (e.g., just those within a particular country; Abel et al., 2019; Zaromb et al., 2014). Rather than relying on small groups constructed in the lab, this approach focusses on the preexisting memories or knowledge that is shared among members of a substantially larger group. This research often focusses on collectively remembered instead of collective forgotten information due to the very large amount of candidate information participants can tap into, although examples exist for studies on collective forgetting, typically when the information set to recall is more constrained (e.g., recall of U.S. presidents; Roediger & DeSoto, 2019). Q11

In general, research leveraging this approach is usually descriptive in nature, focussed on describing what content is shared among large portions of a group without the need for complete overlap and theorising what sort of social factors might influence these collective memories (e.g., Merck et al., 2020; Umanath et al., 2023; Yamashiro et al., 2022). Notably, much of this research relies on some version of the fluency task (e.g., Abel et al., 2017; Burnett et al., 2023; Q12

Öner et al., 2023; Yamashiro et al., 2022; Yamashiro & Roediger, 2021). For example, participants have been asked to recall as many U.S. presidents as they can (DeSoto & Roediger, 2019; Roediger & DeSoto, 2016) or to recall up to 10 important events from World War II (WWII; Abel et al., 2017). While the experimental- and fluency-based research traditions just described both conceptualise collective memory as a shared representation of the past, they differ with respect to the memory system being probed. Many laboratory studies typically aim at overlapping episodic memories; participants encode a common episode, such as a word list, which they are then asked to remember following collaborative recall or discussion (e.g., Rajaram & Pereira-Pasarin, 2010). In contrast, fluency-based explorations often examine overlapping semantic memories; participants generate known people (e.g., U.S. presidents) or events (e.g., WWII; Abel et al., 2019; Roediger & DeSoto, 2014). The common thread across these investigations is a shared interest in the *collective* and how groups of people converge on common representations of memory. We focus our investigation on the second approach as a starting point in the present study.

Fluency Tasks and Collective Memory

As we noted in the previous section, a popular way to tap into the collective memory of a large group of people is to simply ask a sample of respondents to recall some material of interest, for example, WWII events (e.g., Abel et al., 2019; S. Y. Choi et al., Q13 2021; Roediger et al., 2019; Roediger & Zerr, 2022; Zaromb et al., 2013). While the increased use of such fluency tasks to examine collective memory is a relatively recent phenomena in psychology (e.g., Burnett et al., 2023; Öner et al., 2023; Yamashiro et al., 2022; Yamashiro & Roediger, 2021), this work can be traced back to by now a classic study by Roediger and Crowder (1976). In this study, participants were tasked with recalling as many U.S. presidents as possible, either recalling the names in any order, that is, by performing a free recall task, or in the order in which they held office, that is, performing a serial recall task. This study offered insights into the extent to which serial position effects (recalling material from the beginning [primacy] and end [recency] of a list) generalise to the semantic memory domain. This study was revisited roughly 10 years ago in order to address questions about the stability of collective memory (Roediger & DeSoto, 2014). Specifically, in conjunction with other archival data (along with newly collected cross-sectional data), the authors examined the stability of collective memory for U.S. presidents across various age cohorts, which revealed striking similarities across cohorts (e.g., most group members forgetting President Pierce; Roediger & DeSoto, 2014). Interestingly, recall frequencies were highly correlated (correlations between .90 and .99) across different age cohorts, indicating that collective memory is quite stable for such material (DeSoto & Roediger, 2019).

In the past decade or so, other researchers have continued to rely on the use of fluency tasks to examine questions relating to collective memory (e.g., Öner et al., 2023; Yamashiro & Roediger, 2021). For example, Abel et al. (2019) asked people in former WWII Ally and Axis countries to recall up to 10 important events from WWII. This work suggests that there are often a handful of core events recalled by much of the overall sample and significant portions of particular subsamples. For example, with the exception of Russia, people from the former Allied countries recalled several events at similarly high rates (e.g., the attack on Pearl Harbor, the Holocaust). Interestingly, Russians recalled a number of unique events (e.g., the Battle of Stalingrad) at high rates that were not remembered by those in any other country. This methodology has also been leveraged to investigate how people imagine their collective future with a future version of the fluency task (Shrikanth & Szpunar, 2021; Szpunar & Szpunar, 2016). These fluency tasks are used to investigate people's expectations for the collective future (e.g., Burnett et al., 2023; Öner et al., 2023; Peña, 2023; Shrikanth et al., 2018) and typically involve asking people to report the emotional valence of their future projections in terms of negative and positive collective events to characterise collective worries and excitements.

In as much as collective memory is defined as a shared body of knowledge, the content of collective memory is often semantic rather than episodic in nature, that is, consisting of a body of knowledge acquired over time, as in the studies described above, rather than specific instances of experiences one may remember. Importantly, studies that use fluency tasks often tap into knowledge about a topic or semantic memory (e.g., if a large portion of respondents recall a particular event from WWII) rather than episodic experiences about the war. As work progresses to understand the nature of this aspect of collective memory, we explore here how research could benefit from the use of quantitative techniques that have been useful for characterising fluency data in the context of semantic memory research (Morais et al., 2013; Steyvers & Tenenbaum, 2005; see Kumar, 2021, for a review). Specifically, fluency data collected in collective memory research studies could be viewed as a semantic network and thus be suitable for analysing as such. This type of network framing would open the door to novel quantitative perspectives on characterising collective memory. With this goal in mind, we now briefly review how semantic memory research has historically leveraged network analyses to better understand memory more broadly.

Semantic Memory, Fluency Tasks, and Networks

The use of fluency tasks has a long history in psychology (Bousfield & Sedgewick, 1944; Kumar, 2021; Zemla, 2022). In a semantic or category fluency task, respondents are asked to report as many items from a particular category as possible within a particular time limit (Bousfield & Sedgewick, 1944; Zemla, 2022). An important feature of a fluency task is that participants will vary in what they remember, how much they report, and the order of the responses. Of special relevance in the present study are two robust findings. First, some responses appear more frequently than others. For example, responses like *dog* and *cat* are recalled by large portions of respondents when provided with *a four-footed animal* as a category prompt (Henley, 1969; Van Overschelde et al., 2004; also see Zemla & Austerweil, 2017). Second, responses often transition based on semantic relatedness. For example, people are more likely to proceed from *dog* to *cat* than transition from *dog* to *whale*, as *dog* and *cat* share more features and attributes than *dog* and *whale* (Hills et al., 2012; Troyer et al., 1997).

In the present study, we use a fluency task that taps into a single domain of information (rather than a categorised list of information), namely the cities in the United States, where both the frequency and the transition of responses are important components to consider. The frequency component is important because it corresponds to the specific instances that are collectively recalled, that is, what information is reported by a large portion of a sample. Likewise, the transition component is important—and novel—to consider in a collective memory context, that is, how similarly participants might be clustering their recalled cities. For example, a majority of participants may report city A and city B in adjacent positions than city A and city C. In other words, over and above shared content, a focus on common transitions will shed light on the *associations* that are shared among members of a group. Together, these analyses can reveal the similarity in the content as well as the overall structure or composition of collective memory.

Researchers interested in exploring the structure of semantic memory aim to account for the patterns observed in fluency data; many models have been proposed to describe search and retrieval from semantic memory and, relevant to the present study, capture the structure of semantic memory (i.e., how concepts are represented; see Kumar, 2021, for a review). With respect to structure, classic work proposed that much of semantic memory is organised in networks
Q14 (Collins & Loftus, 1975; Collins & Quillian, 1970). In these networks, concepts such as *nouns*, *ideas*, *attributes*, or *features* can be represented as nodes, while nodes are connected either directly or indirectly by edges that index something about the association between the concepts (e.g., semantic relatedness). In this context, a popular approach is to render a semantic network using fluency data; recalled items are represented as nodes, and nodes are connected with edges if they appeared in adjacent positions (often referred to as a co-occurrence network; Zemla, 2022) or nonadjacent but nearby positions (e.g., Goñi et al., 2010). Inspired by the network analysis of fluency task data in semantic memory research, we introduce the application of network analysis in the current work to describe collective memory using data from a fluency task.

To this end, in addition to some traditional analyses, we provide a proof-of-concept network analysis of collective memory patterns in the next section. To undertake this work, we examine novel data that have not been looked at in the current literature. We take the case of collective memory for the U.S. cities among college students in a Northeastern U.S. university. Collective memory for cities is unique from other domains of shared knowledge previously examined in the existing cognitive–psychological literature. For example, as previously mentioned, other studies have examined collective memory for events (e.g., national events before and during the COVID-19 pandemic; Burnett et al., 2023) or for semantic information (e.g., U.S. presidents; DeSoto & Roediger, 2019). In the cities recall task, there are thousands of potential cities for participants to recall, which they can recall in any order they prefer. Network analyses are informative and lead to not only a better understanding of which cities are collectively remembered by participants but, critically, the composition of these collective memories. We now turn to our proof-of-concept network analysis.

Part Two: Proof-of-Concept Collective Memory Networks

Saul Steinberg's famous *View of the World from 9th Avenue*, which appeared on the cover of The New Yorker in 1976, provides a satirical glimpse into how a New Yorker might represent the world. In the image, 9th and 10th Avenue include crisp details such as people, cars, and buildings.[1] Beyond the Hudson River lies New Jersey, depicted as a small strip of land. Going further, the rest of the United States occupies as much space as the distance between 9th and 10th avenues—flat flyover country nestled between Canada and Mexico with the occasional mountain. Only a few cities earn a mention—Washington, DC, Chicago, Kansas City, Las Vegas, and Los Angeles. Finally, China, Japan, and Russia occupy a sliver on the horizon across the Pacific Ocean. While this drawing may be taken as a jab at the Manhattan-centric view of the world some New Yorkers might possess, it encapsulates quite well how schematised representations can be. Whether one is viewing the world from 9th Avenue or their bedroom window in a small Minnesota town, the immediate context is likely to be detail-rich while less relevant concepts blur in the distance, though particularly salient people, places, and events will still cut through the memorial fog. The research on president recall noted earlier supports this general idea (e.g., DeSoto & Roediger, 2019). For example, George Washington is recalled at a high rate by people of all ages/generations (primacy effect), as are recent presidents (recency effect). However, perhaps due to highlighting in the educational system or continued media interest, Abraham Lincoln is also recalled at a high rate. At the same time, many presidents are recalled by very few people. Recent research probing collective memory for the American Civil War, WWII, and more recent public occurrences also supports the notion that collective memory can be selective and egocentric (e.g., Abel et al., 2017; Yamashiro & Roediger, 2021).

Here, we explore data that our lab collected over 10 years (2011–2021) for recall of U.S. cities (see Roediger & DeSoto, 2014, for a similar approach with recall of U.S. presidents). We examined these distractor task data drawn from five separate projects to learn more about the stability of collective memory for U.S. cities across time. Probing memory for U.S. cities is conceptually distinct from asking about nationally relevant occurrences or people and thus provides a window into the collective representations of another facet of memory. More specifically, rather than focussing on memory for past events, our approach focusses on the knowledge of the cities that is developed by a shared representation of the social, political, cultural, and economic positions these cities occupy in the minds of a people at a collective level. With the growing interest in a range of assessments of collective memory, these data provide a timely foundation for applying quantitative tools in a novel way and provide unique insight into an emerging area of interest. Further, this data set is well-suited to examine converging collective memory across time, with the fluency task administered across many projects over many years. Finally, and of novel contributions, we draw inferences on not only what is collectively remembered but also the composition of the memories (e.g., clustering and organisation of responses) shared across hundreds of people.

Method

Data Collection

The data analysed here were primarily collected as part of a distractor task within a series of projects. Specifically, except for one subset of the data (Greeley et al., 2024; see Figure 1[A1]), these data were collected as part of a short task inserted between study and recall phases with the goal of controlling for rehearsal of the study material, a common procedure used in memory experiments. Critically, in all projects, people were told to "recall as many cities

[1] It is also worth noting that Steinberg completed a similar drawing years earlier from the perspective of the West Coast (https://saulsteinbergfoundation.org/essay/view-of-the-world-from-9th-avenue/).

Figure 1
Project Details and Popular Responses

(A1)

Project	*N*	Earliest Data	Latest Data	Setting	Total Response	Valid Response
Choi et al. (2014)	162	2011-09-16	2012-04-19	In-Person/Paper	[*M* = 24.12; *SD* = 11.81; *N* = 162]	[*M* = 22.56; *SD* = 10.44; *N* = 159]
Peña et al. (Under Review)	93	2019-02-19	2019-11-25	In-Person/Typed	[*M* = 25.12; *SD* = 13.05; *N* = 91]	[*M* = 23.73; *SD* = 12.16; *N* = 91]
Greeley et al. (2022)	95	2020-08-26	2020-11-18	Remote/Typed	[*M* = 25.41; *SD* = 12.21; *N* = 95]	[*M* = 24.73; *SD* = 11.88; *N* = 95]
Greeley et al. (Current)	98	2020-10-29	2020-12-03	Remote/Typed	[*M* = 21.22; *SD* = 14.67; *N* = 98]	[*M* = 20.73; *SD* = 14.36; *N* = 98]
Pepe (2021)	182	2021-02-01	2021-05-01	Remote/Typed	[*M* = 28.84; *SD* = 16.29; *N* = 182]	[*M* = 27.71; *SD* = 15.62; *N* = 182]

(B1)

	Choi et al. (2014)	Peña et al. (Under Review)	Greeley et al. (2022)	Greeley et al. (Current)	Pepe (2021)	Overall Proportion
New York City	0.893	0.857	0.968	0.939	0.951	0.923
Los Angeles	0.780	0.813	0.884	0.867	0.929	0.858
Chicago	0.616	0.648	0.758	0.684	0.808	0.709
Boston	0.667	0.626	0.726	0.602	0.753	0.685
Miami	0.654	0.714	0.695	0.541	0.736	0.675
Las Vegas	0.604	0.593	0.716	0.531	0.637	0.618
San Francisco	0.547	0.582	0.653	0.480	0.709	0.605
Houston	0.497	0.495	0.642	0.622	0.632	0.578
Seattle	0.371	0.473	0.695	0.531	0.654	0.542
Dallas	0.403	0.505	0.621	0.673	0.566	0.541
Philadelphia	0.503	0.473	0.600	0.551	0.549	0.534
Albany	0.528	0.495	0.474	0.337	0.549	0.491
Washington D.C.	0.478	0.549	0.547	0.367	0.495	0.486
Austin	0.308	0.473	0.600	0.418	0.560	0.467
Atlanta	0.390	0.462	0.495	0.378	0.538	0.458
San Diego	0.327	0.385	0.558	0.520	0.522	0.458
Orlando	0.403	0.560	0.389	0.337	0.407	0.414
New Orleans	0.346	0.407	0.421	0.306	0.429	0.384
Detroit	0.314	0.275	0.432	0.388	0.407	0.365
Buffalo	0.352	0.341	0.316	0.245	0.418	0.347
Denver	0.189	0.374	0.400	0.306	0.418	0.333
Phoenix	0.208	0.187	0.411	0.337	0.374	0.304
Portland	0.138	0.242	0.400	0.306	0.418	0.301
Pittsburgh	0.302	0.209	0.305	0.265	0.346	0.296
Baltimore	0.258	0.275	0.284	0.245	0.352	0.290
Salt Lake City	0.289	0.275	0.295	0.194	0.236	0.258

COLOR

Note. (A1) Project-level details, including dates of data collection and how the study was conducted (e.g., lab or online). The sample sizes in the rightmost column (*Valid Response*) are used throughout the analyses for computing frequencies; these sample sizes include participants who recalled at least one location that (a) matched a response in the census and (b) that the independent coders agreed on; (B1) project-level and overall recall frequencies for the "Popular Cities" (cities recalled by ≥25% of the overall sample [$N = 625$]). *New York City* was the most popular overall, with over 92% of all participants
Q15 recalling it. Los Angeles was a close second, while Chicago was a distant third. Note that across projects, recall frequencies were relatively stable (for correlations, see Supplemental Table S1).

within the United States as you can for the next 7-minutes." In essence, this task is akin to a time-constrained category fluency task (Bousfield & Sedgewick, 1944). Figure 1(A1) provides a basic overview of the projects from which these data were drawn, including the key task details (e.g., setting, time period) and frequently recalled cities, while the Supplemental Materials include additional project-level details not directly relevant to the goals of the current report. All project-specific procedures and the use of these data in the current context were approved by the Institutional Review Board at Stony Brook University.

Several features of these data are particularly noteworthy. First, these data stem from projects conducted as early as 2011 and as recently as 2021. From a collective memory perspective, this type of coverage provides a rare opportunity to examine collective memory stability. That is, we can ask whether the same cities are recalled at similar rates across time and in different testing contexts (*content stability*), in addition to whether retrieval strategies are shared in a similar fashion (*associative/organisational stability*). Second, these data stem from projects focused exclusively on Stony Brook University undergraduate students, a large state university in New York. As such, we have a clear collective—college-aged students enrolled in a university that is based in the Northeast United States. These participant samples provide a consistent point-of-reference such that any memory changes across time are unlikely to reflect changes in sample demographics. These data also offer an anchor point for future studies, such as those that may focus on different locations, to examine how different social, cultural, and geographical perspectives drive similarities and differences in the development of collective memory.

Data Processing and Validation

With hundreds of participants and considering that all responses were typed or written, variance in spelling ability, typing ability, and general attention to detail was expected. Thus, the fluency data from each project noted above were pooled in preparation for a manual review by two independent coders. For every unique response, each coder provided what they perceived to be the technically correct response, using the internet as needed. For example, the response *albuquirky* was assigned *Albuquerque* by both coders. In the event that a unique response actually held multiple responses (e.g., if a participant did not separate city responses with a typical delimiter), each coder remedied this by adding delimiters. This first-pass manual review served to retain as much data as possible—instead of ignoring idiosyncratic responses, we kept everything. The concordance between coders was high (88% agreement on unique responses); across the combined data we share (16,536 rows), the independent coders agreed on 96.70% of all responses. The Supplemental Materials include more detail on this initial processing phase.

With every original response associated with a spell-checked response, the pooled data were further processed to ensure that, when possible, each participant had one contiguous sequence of responses. Further, we applied two broad inclusion criteria. First, we included only participants who provided usable data in the project from which they were drawn. Second, when email addresses were available (three projects), they were cross-referenced across projects to ensure that they did not complete the task in multiple studies. This was rare (seven participants), and when it occurred, we retained the data from the first instance of participation. If participants did not provide email information in these projects, they were excluded (N = 21). Together, these criteria were applied to ensure that (a) participants were likely to have been attentive throughout the tasks and (b) that responses were not contaminated by practice effects. Applying these criteria, we report on data from 625 participants who provided at least one valid response (see Figure 1[A1]).

Scoring and Analytical Approach

Scoring a response as "valid" (see Figure 1[A1]) involved two key steps. First, for a given response, the two independent coders had to agree on the reported location. While this was important for establishing a reliable estimate of what a person meant when there was a spelling error, this did not guarantee that the response was a city in the United States. For example, a number of participants recalled states (e.g., *Oklahoma*), fictional cities (e.g., *Vice City*), and other noncities (e.g., *town*, *land*) that the coders agreed upon. Moreover, people often have different notions of what constitutes a "city." For example, people reported New York City boroughs (e.g., *Brooklyn*, *Queens*), neighbourhoods (e.g., *Chinatown*), regions (e.g., *Silicon Valley*), and other types of locations (e.g., *Long Island*) with some regularity. Similarly, city names are often not exclusive to a single state (e.g., *Portland* is a city in Maine, Oregon, and several other states).[2] As a second step, responses were cross-referenced with U.S. census data (2020–2022, Incorporated Places and Minor Civil Divisions; https://www.census.gov/data/tables/time-series/demo/popest/2020s-total-cities-and-towns.html). If the response was present in the census, it was counted as correct. Additional details on this process are included in the Supplemental Materials.

Transparency and Openness

This project was not preregistered, and all analyses were conducted in an *ad hoc*, exploratory fashion. Data and code (Greeley et al., 2024) to reproduce the analyses and visualisations are available on the Open Science Framework (https://osf.io/k3x9y/?view_only=0bc8ea9b24de45b692ab49c81b77da90). All analyses were conducted with R (R Core Team, 2021). Q16

Results

We present the results in two main sections. In the first section, we present a largely descriptive overview of the data, consistent with much of the collective memory literature leveraging this approach. In addition to this descriptive overview, we present two novel approaches to analysis. One focusses on characterising city recall frequency across time and testing modality, while the other focusses on characterising the order of city responses across time and testing modality. Thus, both of these analyses are geared toward indexing collective memory as well as the extent of overlap in retrieval strategies. In other words, are the same cities recalled at similar rates and in a similar order across projects? Here, strong positive correlations would suggest that collective memory for U.S. cities is stable for undergraduate students across a decade.

In the second section, we construct networks (i.e., co-occurrence networks) for each project in which cities (responses) are represented as nodes, and edges capture the association between cities (operationalised as transitions between responses) in order to demonstrate the value of this technique. This approach affords a richer view of the data because it brings attention to the memory composition; in other words, examining the degree to which participants are remembering cities in adjacent positions (e.g., whether participants are reporting *New York* next to *Boston*). As such, we analyse the frequency with which particular cities are associated/clustered during retrieval and assess whether these patterns are stable across time and testing contexts. Likewise, we report a variety of network-level descriptive statistics and consider if general network structure remains consistent across time.

Descriptive Overview and Recall Frequency Analysis

Across all participants, 988 unique responses were identified. Of these, 821 responses matched a census location (town, city, state, etc.), while 167 did not. Locations not in the census were quite rare; over 95% of these locations were recalled by less than 2% of all participants. Of those not matching a census location, most appeared

[2] While the majority of responses are relatively clear-cut (e.g., *New York City*, *Los Angeles*, *Chicago*), participants were not required or asked to specify the city/state relationship. As such, it was impossible to be *certain* about what city actually came to mind unless they specified. If they did not specify, for the purpose of scoring as valid or not, all that mattered was coder agreement and that the response appear in the census data.

to be "hamlets" on Long Island (e.g., *Centereach*).[3] These hamlets are unincorporated and do not appear in the census; rather, they are located within townships (e.g., *Brookhaven*) that are represented in the census and cover multiple hamlets and incorporated villages. These nonmatching locations also include responses where participants identified the specific state (e.g., *Portland-Maine*), errant responses (e.g., *Bangalore*), and other location types (e.g., *Cape Cod*).[4] Importantly, across the board, no responses that failed the census-matching check were particularly popular, and as such, they were not factored into these initial analyses. For example, *Tampa Bay* was the most popular nonmatching response, though it was only reported by 34 participants out of 625 (~5.5%).

To facilitate a comparison across projects, we created two popularity bins; cities recalled by more than 25% of the overall sample (i.e., more than 157 people) were deemed *popular*, while cities recalled by between 10% and 24.99% of the overall sample (i.e., between 63 and 156 people) were deemed *moderately popular*. This breakdown is somewhat arbitrary; however, below the 10% cutoff, some projects could provide very little data for comparison. Likewise, as our focus was on collective memory rather than the more unique responses, this seemed to be a sufficiently broad window of inclusion and is generally consistent with the collective memory literature (e.g., Abel et al., 2019; Zaromb et al., 2014).

A core finding was that only a handful of cities were recalled by the majority of participants; most cities were recalled by relatively few participants. Plotting recall frequency as a function of city rank—from most reported to least reported—suggests a power law relationship similar to word frequency distributions of the same type (see Supplemental Figure S2). Specifically, just 26 cities were recalled by ≥25% of the overall sample and deemed *popular* (see Figure 1[A2] for a list). Of these, just 11 cities were recalled by more than 50% of the overall sample. These frequently recalled cities included locations like *New York City*, *Los Angeles*, and *Chicago*. Similarly, 29 cities were recalled by between 10% and 24.99% of the overall sample and deemed *moderately popular*. These cities included locations like *Nashville*, *Minneapolis*, and *San Jose*.

Pivoting to the question of recall stability across projects, we correlated recall frequencies (expressed as the proportion of participants in each project recalling a given city) across each pair of projects for each popularity bin.[5] On the one hand, these correlations suggest that when cities are popular overall, they are recalled at similar rates across time and testing contexts; that is, there is notable stability, with correlations ranging from .81 to .96 (M = .89). On the other hand, and as would be expected, when cities are only moderately popular overall, they are recalled at more variable rates from project to project, with correlations ranging from −.37 to .71 (M = .26). A full list of correlations and their associated statistical information is available in Supplemental Table S1. Beyond recall stability in the frequency of recall, we also asked whether cities were reported in a similar order across projects. To that end, we correlated mean output positions for the cities in each popularity bin across each pair of projects. These correlations generally align with the recall frequency results (Supplemental Table S2).

We also asked about the recall stability across different testing modalities since, across projects, data were collected in the laboratory (on campus at Stony Brook University) or online (wherever the participant happened to be). Echoing the pairwise trends, when focussing on the 26 popular cities, recall rates were similar across modalities, $r = .89$, $p < .001$. When isolating the 29 cities classified as moderately popular, there was not a significant relationship, $r = .04$, $p = .852$. Inspecting what particular cities are more likely to be reported in person versus online, two locations stand out as outliers (see Supplemental Figure S3). *Stony Brook* was recalled by over 25% of laboratory-based participants, but just under 14% of online-based participants. Conversely, *Nashville* was recalled by over 31% of online-based participants, but just under 12% of laboratory-based participants. These results suggest a *proximity preference*, an idea we speculate on further in the General Discussion section.

Proof-of-Concept Network Analysis

We conducted a network-based characterisation of collective memory data, gathered in the context of a fluency task, to explore how this approach might enrich our understanding of collective remembering. To that end, we constructed a number of networks using the combined data set as well as project-specific data sets. Of particular interest was whether associations at retrieval were stable across time and testing contexts. That is, whether there are some collective patterns in memory composition despite the massive set of available responses. This adds a new layer of inquiry beyond content overlap and beyond mean output positions that shines a light on whether retrieval dynamics are shared among members of a collective, thereby resulting in a similar structure or composition of collective memory.

To include as much data as possible and to minimally disrupt contiguous chains of responses, responses were included so long as they were legible and the two independent coders converged on the same response during spell checking. Thus, responses like *Tampa Bay*, which was not in the census, were included in networks to ensure that potentially common associations (e.g., *Miami-Tampa Bay*) were accounted for even if one of the locations was not technically a city/town. Importantly, if a response was not legible or if the coders did not converge on the same response, the contiguous chain of responses was broken, and transitions to/from these invalid responses were not counted. This preparation resulted in an overall network consisting of 988 unique nodes (cities/locations) and 6,373 unique undirected edges (observed recall transitions without respect to order; e.g., *Los Angeles–San Francisco* and *San Francisco–Los Angeles* are not distinct transitions). This network includes data from 625 participants, the same as the total N reported in the aforementioned analyses.

The overall and project-specific networks are visualised in Figure 2, along with a tabular breakdown of the most common

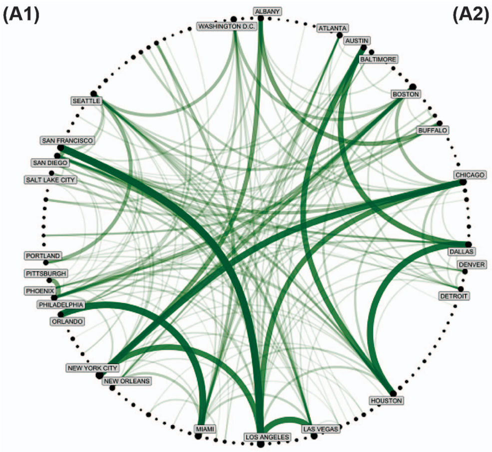
[3] One hamlet that would be classified as moderately popular was Stony Brook (~18.5% recalling), where Stony Brook University is located. Stony Brook did end up matching a location in the census, despite being a hamlet. However, the match was to a small township in Minnesota that has the same name. We note that while other hamlets may have been excluded because of their status, and it is unlikely that participants were referring to Stony Brook, Minnesota, this discrepancy does not have any bearing on the interpretation of our results.

[4] Note that participants rarely explicitly identified the corresponding state. For instance, four people (out of 625) specified Portland-Maine, and four people specified Portland-Oregon. Because these responses were so rare, they were left as distinct locations rather than receiving a special merge with the census data (see the Supplemental Materials for details).

[5] Note that Pearson correlations are acceptable here as the recall rates *within* each popularity bin were normally distributed to a reasonable degree (see Supplemental Figure S1), despite the entire range of city recall rates being very positively skewed as most cities were recalled by relatively few participants (see Supplemental Figure S2).

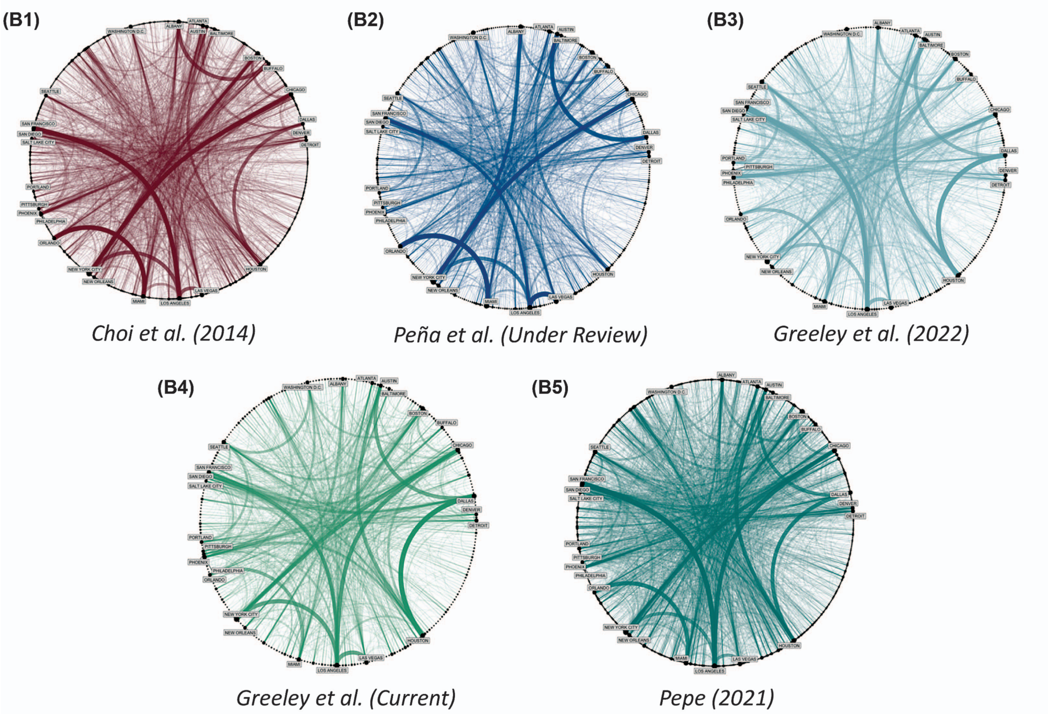
Figure 2
Network Characterisation of the Overall and Project-Specific Fluency Data

(A1)



(A2)

Rank	Undirected Edge	Overall Frequency	Range Information
1	Los Angeles-San Francisco	0.1872	Min = 0.12, in Peña et al. (Under Review) Max = 0.25, in Pepe (2021)
2	Miami-Orlando	0.1696	Min = 0.12, in Greeley et al. (Current) Max = 0.2, in Pepe (2021)
3	Dallas-Houston	0.1616	Min = 0.08, in Peña et al. (Under Review) Max = 0.21, in Greeley et al. (2022)
4	Chicago-New York City	0.1600	Min = 0.13, in Greeley et al. (2022) Max = 0.18, in Pepe (2021)
5	Las Vegas-Los Angeles	0.1488	Min = 0.13, in Choi et al. (2014) Max = 0.19, in Peña et al. (Under Review)
6	Los Angeles-New York City	0.1424	Min = 0.13, in Peña et al. (Under Review) Max = 0.15, in Pepe (2021)
7	Austin-Houston	0.1392	Min = 0.09, in Choi et al. (2014) Max = 0.19, in Pepe (2021)
8	Chicago-Los Angeles	0.1360	Min = 0.07, in Peña et al. (Under Review) Max = 0.21, in Pepe (2021)
9	Austin-Dallas	0.1360	Min = 0.07, in Choi et al. (2014) Max = 0.17, in Pepe (2021)
10	Albany-Buffalo	0.1072	Min = 0.05, in Greeley et al. (Current) Max = 0.13, in Choi et al. (2014)
11	Philadelphia-Pittsburgh	0.1024	Min = 0.08, in Choi et al. (2014) Max = 0.12, in Peña et al. (Under Review)
12	Albany-New York City	0.1024	Min = 0.08, in Choi et al. (2014) Max = 0.14, in Peña et al. (Under Review)
13	San Diego-San Francisco	0.1008	Min = 0.07, in Greeley et al. (Current) Max = 0.14, in Pepe (2021)
14	Los Angeles-San Diego	0.0944	Min = 0.06, in Choi et al. (2014) Max = 0.13, in Pepe (2021)
15	Boston-New York City	0.0944	Min = 0.07, in Pepe (2021) Max = 0.13, in Choi et al. (2014)



(C1)

	Nodes	Edges	Edge Density	Degree Centralization	Betweenness Centralization	Mean Distance	Global Transitivity	Diameter
Overall Network								
Overall	**988**	**6373**	**0.01**	**0.15**	**0.06**	**3.26**	**0.29**	**9**
Project-Specific Networks								
Choi et al. (2014)	575	2331	0.01	0.13	0.09	3.50	0.24	12
Peña et al. (Under Review)	411	1492	0.02	0.13	0.08	3.54	0.24	9
Greeley et al. (2022)	355	1429	0.02	0.14	0.08	3.57	0.29	15
Greeley et al. (Current)	292	1196	0.03	0.14	0.09	3.40	0.28	11
Pepe (2021)	576	2804	0.02	0.15	0.10	3.42	0.29	10

Note. (A1) Combined network representation of the entirety of responses that met our inclusion criteria across all projects. Nodes represent cities, while the undirected edges indicate that the connected nodes were recalled in adjacent positions (e.g., *Los Angeles* and then *San Francisco*, or vice versa). This is in contrast to a directed network that would treat transitions from

(*figure continues*)

COLOR

edges and a summary of several network-level descriptive statistics. Visualising the overall network highlights several key retrieval patterns (Figure 2[A1]), most notably that some transitions are relatively common. The 15 most common edges are listed in Figure 2(A2). For example, *Los Angeles* and *San Francisco* were recalled in adjacent positions by nearly 19% of all participants, while cities like *Austin*, *Houston*, and *Dallas* were also frequently recalled in pairs. This suggests people are frequently using geographical clustering as one strategy to help aid their recall. At the same time, another collective strategy being used is the perceived population or importance of the city (e.g., *New York City*, *Chicago*, and *Los Angeles* were also quite common). Visualising the project-specific networks in the same fashion (Figure 2[B1–B5]) highlights that many of these associations generalise across time and testing contexts. Finally, a breakdown of the network-level characteristics (Figure 2[C1]) suggests that the project-specific networks are structurally similar to one another; the largest differences are in node and edge counts, which makes sense in light of the sample size differences.

To quantify the associative (edge weight) stability across projects, we isolated the edges common to all projects ($N = 180$ edges) and correlated the log-transformed weights between each pair of projects. In brief, these analyses suggest that associations at retrieval are very stable across time and projects (see Supplemental Figure S4[A1]). Q17 Specifically, correlations ranged from $r = .52$ to $r = .65$, and all FDR adjusted p values were significant (ps $< .001$). Finally, visualising the degree distribution for each network provided additional evidence that networks were structurally similar and, specifically, that they have a small world structure typical of semantic networks (Steyvers & Tenenbaum, 2005; Supplemental Figure S4[B1–B6]).

General Discussion

In the current work, we reflected on how memory research across the social sciences has traditionally examined collective memory, the different approaches to assessing collective memory within the cognitive–psychological literature, and how we can leverage analytical tools from the semantic memory literature—namely network analyses—to explore some characteristics of collective memory using data from fluency recall tasks. We then examined collective memory for U.S. cities in different samples of participants across a 10-year period. We observed a striking stability: People reported cities at a similar rate across time and task contexts (i.e., laboratory and online studies), and they often retrieved cities in a similar fashion. This pattern was particularly salient when focussing on cities that were popular overall in our sample (recalled by ≥25%). As would be expected, this stability was reduced when considering less popular cities and was particularly evident when comparing projects on a pairwise basis and when binning studies into laboratory- and online-based modalities.

Our novel network-based characterisation of these data suggests that participants often retrieved major cities and geographically similar cities in adjacent positions (e.g., *Los Angeles–San Francisco*). Finally, comparison of project-specific networks suggests that these retrieval patterns are stable across time and task contexts. Overall, this network-based approach provides a novel lens through which to view the contents and composition of collective memory.

Qualitatively, our results are consistent with other collective memory projects relying on a fluency methodology (e.g., Abel et al., 2019) in that a small minority of responses were recalled by the majority of participants. We found that these cities were recalled at very stable rates and in similar mean output positions across time and projects. However, focussing on less popular cities, we note a sharp decline in recall frequency stability and a slight decline in mean output position stability. First, the general finding that relatively few cities are recalled by a large portion of the people is reasonable given that there are thousands of cities available to report. At the same time, it is quite striking how stable recall frequency and mean output positions are for these cities.

Our novel application of network analysis afforded a deeper dive into the stability of the composition of these collective memories across time. For the combined data and for each subdata set, we constructed networks consisting of cities (nodes) and edges defined by the observed recall transitions. The visualisations and edge-weight correlations point to a remarkable stability. Across the board, several transitions consistently emerge at high rates, suggesting that some associations at retrieval are resilient to the passage of time and changes to procedure (i.e., in person vs. online data collection). More broadly, this analysis revealed how collectively recalled cities were collectively clustered by participants.

We view our exploratory application of network analysis as a rich source of insight for collective memory researchers. Collective memories of U.S. cities, a domain quite different from the other more traditionally studied domains, provide an ideal starting point and demonstration of the application of this approach. Network analyses can be applied to other domains of shared knowledge,

Los Angeles to *San Francisco* as distinct from transitions from *San Francisco* to *Los Angeles*. The size of a node represents how often a city was recalled, with larger nodes indicating greater remembrance. The thickness and colour density of the edge represent how frequently the two cities were reported consecutively, with thicker/darker lines indicating a greater occurrence of pairwise clustering. The network is simplified for interpretability such that only cities recalled at least once in every project are depicted as nodes, and edges are only included if that particular transition was made at least once in every project. (A2) A list of the most frequently occurring transitions/associations (i.e., highest edge weights). *Los Angeles–San Francisco* (undirected) was the most common pairing, present in nearly 19% of participants' responses. Edge weight range information across projects is provided in the rightmost column. (B1–B5) Project-level network visualisations. Again, cities are represented as nodes, while edges indicate that the connected nodes were recalled in adjacent positions; edge colours are project-specific to add contrast between networks (dark red = H. Y. Choi et al., 2014; dark blue = Peña et al., 2024; light blue = Greeley et al., 2022; light green = Greeley et al., 2024; teal = Pepe, 2021). Several patterns are visually present across all projects, suggesting that retrieval unfolds in a relatively stereotyped fashion across time and testing contexts. (C1) Network descriptive statistics for the overall network (green) and project-specific networks.

including foundational memories, WWII memories, and much more, and are likely to prove productive for yielding important insights. For instance, network analyses are a powerful tool to reveal not only which events people might remember about their group's past but also the composition of these memories, which could help uncover a larger narrative about how people view the collective past. One might be able to observe if people are clustering based on events that contribute to an egocentric narrative; for example, examining whether people are clustering events related mostly to their own geographical region when prompted to recall events most foundational to the United States (for an example of collective narcissism, see Putnam et al., 2024). For instance, would participants living in southern states such as Alabama or Texas report northeast cities such as Albany or Buffalo in the fluency task used here? This unlikely outcome, by the same token, delineates the notion of collective memory as a shared pool of knowledge influenced by shared environments. Cities like Albany and Buffalo making the "popular cities" list in our data capture the shared geographical (and
Q18 egocentric) influences on collective memory (see Putnam et al., 2018, for the notion of collective narcissism). In this sense, what may be considered a limitation of sampling conversely helps us to understand how shared geographical environments shape shared representations, a perspective that resonates with recent works reporting on state-level biases people exhibit for collective narcissism for their states' contribution to American history (e.g., Putnam et al., 2018). Overall, the application of network analyses may provide unique answers to numerous questions that are of interest to cognitive psychologists.

Network analyses also created a conceptualisation of how collective memories are organised, a concept known as *collective*
Q19 *retrieval organisation* (Greeley & Rajaram, 2022). As we mentioned earlier on, conversations and discussions facilitate the emergence of collective memories (Rajaram et al., 2022). Emerging evidence suggests that social interactions not only synchronise what we remember but also how we organise these memories in relation to one another (Congleton & Rajaram, 2014). In other words, people remember similar information in similar orders after discussing information with other people (Greeley et al., 2022). Therefore, we see an emergence in collective memory and collective retrieval organisation via social interactions. In the case of the present study, we asked people to report U.S. cities without any prior interaction, and we see that people with shared identities (i.e., being undergraduate students in the same university) are reporting similar cities in strikingly similar orders. Therefore, the benefits of using network analyses as a tool to explore *collective retrieval organisation* and reveal larger patterns about the composition of memories are both intriguing and compelling.

Limitations

We note some limitations of the present study. First, data collection for each project occurred during time frames that prevented a test of how specific major occurrences might shift recall rates and city associations. For example, although the Greeley et al. (2022) project was conducted during fall 2020, a period marked by the 2020 Presidential Election and the COVID-19 pandemic, we could not capture whether specific events prompted quick and short-lived shifts in responses because data collection unfolded over months, not days or weeks. At the same time, we were able to collect a considerable amount of data across 10 years and that timeline bolsters the pattern of stability in recall over a longer period. In future work, it would be interesting to assess how major historical events may shift collective memories at both short and long intervals.

Second, three of the five projects included in the present study were conducted entirely online, giving participants the option to complete the study from any geographic location of their choice or availability. However, not having had access to the participants' locations, we could not examine how geographical location might also have influenced recall of U.S. cities. Intuitively, for example, one might be more likely to report cities in New York state if they are completing the task at Stony Brook University. This idea is supported by our modality-specific analyses. Specifically, *Stony Brook* was reported at a much higher rate when data collection took place in the laboratory, suggesting a proximity preference, similar to a region-specific bias reported in the study of collective narcissism (Putnam et al., 2018). While we cannot examine where online participants completed the task, about half of undergraduate student population at Stony Brook University commutes to campus, suggesting they reside in New York state. At the same time, international students also represent about 13% of the student population from Stony Brook, and it is unclear where these students may have completed the task.[6] Thus, we do not have a strong sense for how these results might generalise outside of New York state or whether responses might depend on the respondents' location when completing the task.

Last, as noted above, all five projects sampled from undergraduate students enrolled at a public university in the Northeast United States. This is a strength in that we have a relatively stable population from across a decade. Likewise, the student body at Stony Brook is somewhat more diverse than at many universities (https://datausa.io/profile/university/stony-brook-university). But there are also some limitations to consider. Even though the people in our study came from many diverse backgrounds (e.g., about 21% of the participants reported that they are not native English speakers; see Supplemental Materials) and were enrolled in a university with students from all over the country and globe, more people we sampled identified as either White or Asian in comparison to other identities (such as Black or African American, Hispanic/Latino, and Native American). As noted by cultural psychologists, the overrepresentation of some groups and not others, a pattern prevalent in psychological research, poses some generalisability issues (Henrich et al., 2010; Wang, 2021). Greater diversity in the composition of the samples (see Roberts et al., 2020) in future work would enable researchers to explore how a variety of racial and cultural groups remember their collective past and will ultimately help us understand individual differences as well as universal principles of individual and collective cognition (see Gutchess & Rajaram, 2023; Thomas, 2023). In a similar vein, our samples were largely young adults. Recruiting more middle-aged and older adults in studies will help explore the generalisability these phenomena across the adult lifespan, especially given work on some age and age cohort differences in collective memory (e.g., Burnett et al., 2023; Zaromb et al., 2014).

[6] For more information, see: https://www.collegefactual.com/colleges/stony-brook-university/student-life/international/.

Concluding Thoughts

To conclude, we propose that collective memory research would benefit from the use of network science; whereas research so far has focused almost exclusively on what people recall, adopting a network perspective provides additional insight by revealing how similarly retrieval unfolds across members of a group. To illustrate this point, we leveraged data from a variety of projects conducted over a period of 10 years to examine collective memory for the U.S. cities. Across several correlational analyses, we find that some cities (those that are popular overall) are recalled at similar rates and in similar output positions across time and project contexts. Novel to the present study, an initial, proof-of-concept network approach suggests that recall transitions (e.g., recalling *Los Angeles* and *San Francisco* in adjacent positions) are made at similar rates as well. These results converge and suggest a remarkable stability in both what people recall and how retrieval unfolds, providing a window into the composition of collective memories.

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Received February 7, 2024
Revision received July 3, 2024
Accepted July 29, 2024 ■

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