Networks of the Future: Mapping Collaboration, Fragmentation, and Integration in Psychological Science

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Abstract

As psychological science approaches its next century, growing fragmentation threatens its coherence as a unified discipline. This study applies social network analysis to coauthorship networks in an emerging interdisciplinary area — human-AI teaming — to examine whether increased research output fosters integration or isolation. Analyzing 2,860 authors across 966 publications (2003-2025), we find severe fragmentation: only 19% of authors belong to the giant component, with overall network density of 0.002, meaning 99.8% of possible collaborations never occur. Despite high local clustering (transitivity = 0.82), the network lacks small-world properties, with average path length of 5.45 and diameter of 15 within the giant component. Exponential random graph models reveal strong homophily effects, with collaborations 967 times more likely within the same institution and 70 times more likely within the same subject area. Temporal analysis shows accelerating fragmentation: the network grew 76% from 2022 to 2025. but the giant component shrank proportionally from 6.6% to 4.4%, while institutional homophily shifted from cross-institutional collaboration to extreme same-institution clustering. These findings suggest that without structural interventions rewarding cross-cluster collaboration, psychology risks splintering into disconnected micro-specialties rather than maturing into an integrated interdisciplinary science.

Keywords: bibliometric, social network, coauthorship, human-AI teams

Networks of the Future: Mapping Collaboration, Fragmentation, and Integration in Psychological Science

As psychological science looks toward the year 2125, one of its greatest challenges will be overcoming its growing fragmentation. Fields that once shared similar foundations now operate in silos, with researchers often co-authoring only within narrow subcommunities (Luke et al., 2015; Tight, 2025). These problems are inflated by exponential growth in publications: The Economist (2024) reported that new academic publications have doubled since 2010. At the same time, public trust in science is shaken as peer-reviewed articles become fraught with biases and ethical violations (Teixeira da Silva & Dobránszki, 2015; Vazire, 2018; Hernandez, 2025).

The present study addresses a core question: as research output increases, is scientific knowledge increasingly fragmented across silos, or are scholars collaborating across disciplinary lines to share discoveries more efficiently? This paper argues that the future of psychological science depends not only on new discoveries, but on restructuring how knowledge spreads: from isolated subfields to integrative, interdisciplinary networks. We apply social network analysis (SNA) to co-authorship networks for an exemplar topic (human-AI teams), demonstrating how these methods map idea diffusion and predict collaboration patterns.

A Review of Bibliometric Methods

Bibliometric methods quantitatively examine vast research datasets by focusing on publication attributes (authors, keywords, citations) rather than paper content. While traditional systematic reviews identify and thoroughly analyze subsets of papers, bibliometric methods leverage online databases (Web of Science, Scopus) to understand the state of scientific knowledge. In their review and how-to guide for bibliometric analysis, Zupic and Cater (2015) call this out as a wide-open field of opportunity for researchers to use bibliometric methods to better understand the state of scientific knowledge in a field of study — particularly in the psychological sciences. Broadly speaking, bibliometric methods can be applied to focus on citation networks (which article cites other articles), keyword networks (which words appear with other words), and coauthorship networks (which author publishes with other authors). Historically, most bibliometric studies have focused on citation networks (Zupic & Cater, 2015), which quantify an article's degree of influence based on how many citations it garners. Co-citation analysis takes a step further by assessing the frequency with which two articles are cited together, thus implying that the papers discuss similar topics or report similar findings. This allows scholars to visualize and describe co-citation networks of papers that are frequently cited together, creating clusters of papers that could be described as taking a similar theme, approach, or finding on a given research topic.

Two notable examples of co-citation analyses in the psychological sciences are Vogel et al. (2021) on leadership development and Reichard et al. (2025) on psychological capital. Vogel et al. (2021) examined 2,390 primary documents on leadership development along with the 78,718 secondary documents that these primary documents cited. Given the size of their dataset, they focused on the top 100 documents (based on number of citations) and analyzed how the top 100 primary documents cited one another over time, along with content coding of these documents to articulate themes of leadership development research that are most prominent in the network. As a second example, Reichard et al. (2025) examined 937 primary documents citing 28,428 secondary documents and focused on content coding of co-citations of secondary documents (again focusing on the top 100). These two examples illustrate how bibliometric methods have been used to understand the network of knowledge foundations and scholarly research, in two specific psychological areas, by focusing on the network of *cited articles* (i.e., secondary documents).

More recently, bibliometric studies have looked at co-authorship networks, which is the focus of the present study. To our knowledge, none of these methods have been applied to the psychological sciences. Examination of coauthorship networks is advantageous compared to citation networks in that it “can provide evidence of collaboration and produce the social structure of the field” (Zupic & Cater, 2015, p. 432). Although coauthorship does not always mean equal collaboration, it allows us to focus on the social network of knowledge rather than citation influence alone.

Outside psychology, exemplar coauthorship studies demonstrate its impact on understanding fields of study. Newman (2001) examined over 2 million authors in seven specific biomedical, physics, and computer science databases. All results (except the smallest database) showed one large cluster of authors who regularly collaborate, comprising of over two-thirds of all authors. In all cases, most authors had fewer collaborators, with a handful having many. This phenomenon was also found in analyses of University of Florida authors (Sciabolazza et al., 2017), authors in tourism and hospitality research (Ye et al., 2013), and Academy of Human Resource Development authors (Chae et al., 2020). Other patterns of findings include low density coauthorship networks (0.001 in Chae et al., 2020 and Sciabolazza et al., 2017), which means that just 0.1% of all potential coauthorship connections among the thousands of authors in each dataset were realized. Additionally, some papers examined probabilities of coauthorship based on factors such as prior publications and author gender among computer science researchers (Zhang et al., 2018) and even physical location of their offices among University of Florida researchers (Sciabolazza et al., 2017). Finally, one interesting paper (Whetsell, 2023) examined coauthorship at the *country* level (i.e., each country is an "author") to show how international collaborations have increased over time. Put together, these examples illustrate how valuable coauthorship analysis is, but also highlight the many unrealized opportunities to apply such methods to understanding how knowledge spreads in the psychological sciences.

Social Network Theories in Coauthorship Networks

Importantly, social network theories explain why coauthorship networks illuminate knowledge diffusion in the 21st century of psychological science research (Borgatti et al., 2009; Methot et al., 2022). Of note is the small-world effect: "that most pairs of people in a population can be connected by only a short chain of intermediate acquaintances, even when the size of the population is very large" (Newman, 2001, p. 404).[1] Several studies have found this in coauthorship networks, such that most authors are connected, within a few degrees of separation, to a central "hub" of authors (Newman, 2001; Ye et al., 2013; Chae et al., 2020). If the small world effect holds true for the psychological sciences, it illustrates how the *core* of knowledge diffusion in the psychological sciences resides in or begins with a handful of authors. Such a finding is critical because it suggests that knowledge can spread relatively quickly even if the overall network structure is highly clustered. This necessitates the identification of central actors, often referred to as "bridges", who possess high degree or betweenness centrality, as they are the key individuals enabling these short paths for knowledge exchange and potential cross-pollination within the research area.

A second set of network theories focus on understanding who is likely to publish with whom: (1) homophily, the tendency to publish with similar others; (2) transitivity, publishing

[1] In pop culture, the "Six Degrees of Bacon" rates actors by how many links separate them from Kevin Bacon (a score of 1 means they appeared in a film with him, 2 means they appeared with someone who did, and so on). In mathematics, the Erdős number works the same way for coauthorship (a score of 1 means publishing with Paul Erdős, 2 means publishing with someone who has, and so forth).

together if connected to a common author; and (3) preferential attachment, publishing with already well-connected authors (Zhang et al., 2018). Sciabolazza et al. (2017) found evidence of homophily and transitivity in their analysis of University of Florida faculty, such that authors tended to work with colleagues similar in tenure status, disciplinary field, and even age or gender. Freeman and Huang (2015) specifically examined ethnic identity across authors from 2.5 million scientific papers; although they did not take a social network analysis approach, they found that persons with similar ethnicity tended to coauthor together. If these effects are also found in coauthorship networks in the psychological sciences, it points to severe limitations in the effective and efficient spread of knowledge. Homophily, transitivity, and preferential attachment tend to reinforce the formation of cohesive, tightly-knit groups or cliques, thus limiting the diversity of ideas across coauthors. At scale, this can lead to the field's growing fragmentation and isolation into silos, where researchers coauthor only within narrow subcommunities.

Finally, structural holes and weak ties theories may counter homophily and transitivity effects. Structural holes refer to absences of a tie between two authors when they are both connected to a third, focal author (i.e., the absence of transitivity). An author who is the "boundary spanner" or "broker" between two structural holes gains social capital benefits by bridging fragmented clusters or silos. Without them, even the largest cluster of coauthors could break into smaller, disconnected components, leading to a loss of knowledge transfer within the broader network of authors. By examining the degree to which these effects are seen in the coauthorship network for psychological sciences, we can better understand the degree to which psychology may be benefiting from a diversity of perspectives in scientific research.

In summary, bibliometric methods have a long history that has largely focused on citation analyses; a few studies have focused on coauthorship networks and laid a foundation for the present study, but none have applied such methods to the psychological sciences. Moreover, several relevant network theories have informed our understanding of why and how coauthorship networks reflect the state of knowledge diffusion and collaboration in scientific research. Thus, the present study seeks to address the following research questions, formed based on the extant studies of coauthorship networks in other fields of study, combined with the aforementioned network theories. Of note, following the example of prior studies (e.g., Zhang et al., 2018; Chae et al., 2020), in order to keep the network a small enough size for visualization and analysis, we focus on a specific topic within the psychological sciences: human-AI teams.[2]

RQ1. What are the structural characteristics of the coauthorship network for research in the psychological sciences, and what does that tell us about the future of research?

RQ2. To what degree are effects such as the small-world phenomenon, homophily and transitivity and preferential attachment, and structural holes and weak ties prevalent in this coauthorship network, and what does that tell us about the future of research?

RQ3. How has the network structure changed over time?

Methods

[2] To be clear, the choice of topic is not the focal point of this study; any topic within the psychological sciences could be studied. However, we chose "human-AI teams" because of its rapid and recent growth in relevance and scholarly interest, thus indicating that it is likely to become an important topic in the next 100 years. Additionally, this topic benefits from research outside of the psychological sciences (e.g., computer science) *in collaboration* with psychology researchers; thus, it allows us to test the degree to which homophily of field of study is relevant. Finally, this topic is recent, with a few early articles beginning in 2021 followed by exponential growth. This allows us to answer RQ3 by focusing on papers from 2022 (first year of substantial research publications, before ChatGPT was released) and 2025 (most recent year of research). The same methodology proposed in this study can be replicated simply by changing the key terms of the search parameters to explore how the network changes in other subfields of psychology.

This study utilizes social network analysis to explore the topological features of our co-authorship network. The network is a graph where nodes represent authors and edges represent a collaborated publication. We draw our data from Scopus using a search query that includes aliases and truncated forms of "human-AI teaming" to capture variations of the term in the literature. Scopus is well-suited for co-authorship network analysis due to its comprehensive metadata and compatibility with bibliometric tools. Scopus returned any types of published documents containing at least one of the specified variations of the keyword either included in the abstract, title, or keywords. With a focus on the topic of human-AI, the initial search returned 986 records from 2003 to 2025. We scraped data including important variables like author names, study title, publishing year, journal name, DOI, affiliations, citation count, and subject area. A multi-step data cleaning process was applied: normalizing DOIs, removing duplicate papers, standardizing (including merging author aliases by name-matching) and retaining documents with valid DOIs. For aliases that could not be resolved by matching the first names with initials, the process was handled through manual review of author names. After our cleaning and deduplication, we ended up with a dataset of 2860 unique authors on 966 publications.

For visualizing the network, we utilized VOSViewer's software, which employs a distance-based layout, association-strength normalization, the Smart Local Moving algorithm for clustering, and the "visualization of similarities" mapping technique. A more detailed discussion on VOSViewer's techniques is provided by Van Eck et al. (2010). We focus on the largest connected component, following the standard practice of prior bibliometric studies, since graph-based methods are not suitable for visualizing networks as large as our full co-authorship dataset (e.g., Vogel et al., 2021; Reichard et al., 2024).

To address RQ1, we explored the network properties, including both descriptive metrics, component analysis (i.e., subgroups of connected coauthors within the larger network), and application of the power law distribution test (Clauset et al., 2009), to better understand the structure of the coauthorship network and its implications for the future of psychological science.

To address RQ2, we use Exponential Random Graph Models (ERGMs) in a social network analysis (Robins et al., 2007). ERGMs model the probability of the existence of a tie between two authors (i.e., collaboration) based on some set of predictor variables. ERGMs can be used to test, as predictors, both attributes of a node (e.g., author disciplinary background, author productivity) and structural elements of the network (e.g., triangles, degrees; for details, see Lusher et al., 2013). Thus, we apply ERGMs to address our RQ2 of the degree to which author similarities and transitivity (or lack thereof) influence the likelihood of collaboration.

Finally, to address RQ3, we compared the results from RQ1 and RQ2 between publications from 2022 (first year of substantial research publications, before ChatGPT was released) and 2025 (most recent year of research).

Results

Visualizations and Descriptive Analyses (RQ1)

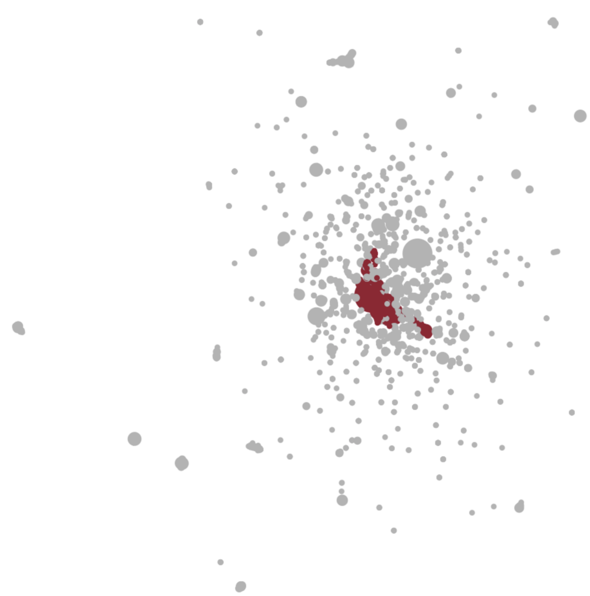
To answer RQ1, we explored the network properties of the 2860 authors which included 8485 coauthorship ties as shown in Table 1 and Figure 1. The results exhibit severe fragmentation of the coauthorship network with science conducted in silos. The network has 475 components and a density of 0.002, meaning that 0.2% of all possible coauthorship ties between the 2860 authors were realized. Moreover, only 540 (19%) of authors are in the largest connected component. Interestingly, transitivity is high (0.82), suggesting that when authors do collaborate, they form cohesive triangles within their local clusters. This pattern of high local clustering combined with extreme global fragmentation indicates that the field operates as hundreds of disconnected small authorship teams rather than a larger interconnected group of researchers.

Table 1. *Network properties for entire coauthorship network (unweighted edges).*

nodes	edges	isolates	components	gc_nodes	density	avg_degree	transitivity
2860	8485	64	475	540	0.002	5.9	0.82

Notes: isolates = solo authors with 0 degree (i.e., no coauthorship ties); components = number of connected subgroups within the network; gc_nodes = number of authors in the largest component; density = measure (scale of 0 to 1) of how interconnected the network; avg_degree = average degree (i.e., number of coauthorship connections) an author has; transitivity = measure (scale of 0 to 1) of overall tendency for a network's nodes to form triangles (AKA global clustering coefficient).

Figure 1. *Visualization of the whole coauthorship network.*



Notes: The size of nodes are weighted based on the authors' total publications. Edges (i.e., coauthorship ties) are represented as lines connecting nodes, but the size of the graph makes them difficult to see. The giant component is highlighted in red.

Degree distributions can be used to check for the "scale-free" property, which is one with many low degree nodes and a few nodes that are highly connected (Barabási & Albert, 1999).

This would mean a small number of authors that have many co-authorships, but the remaining authors having fewer connections. Figure 2 shows that 95% of authors have fewer than 17 collaborators (M = 5.9), with a long tail out to a maximum of 54. Using the poweRlaw package (Gillespie, 2015), we found that a power law provides a reasonable fit for degrees $k \geq 7$, with export $\alpha = 3.18$ (95% CI: [3.03, 3.37] and $R^2 = 0.70$ (Figure 3). This finding aligns with the network's fragmented state: rather than a hub-dominated structure where central figures facilitate knowledge exchange, the network consists of many small, relatively balanced research teams operating in isolation. The power law exists only with more connected authors (degree greater than 7), but the high exponent (especially compared to other coauthorship networks that are usually around 2; Newman, 2001) indicates that even well-connected authors have limited reach across the fragmented landscape.

Figure 2. *Degree distribution of authors in the unweighted network.*

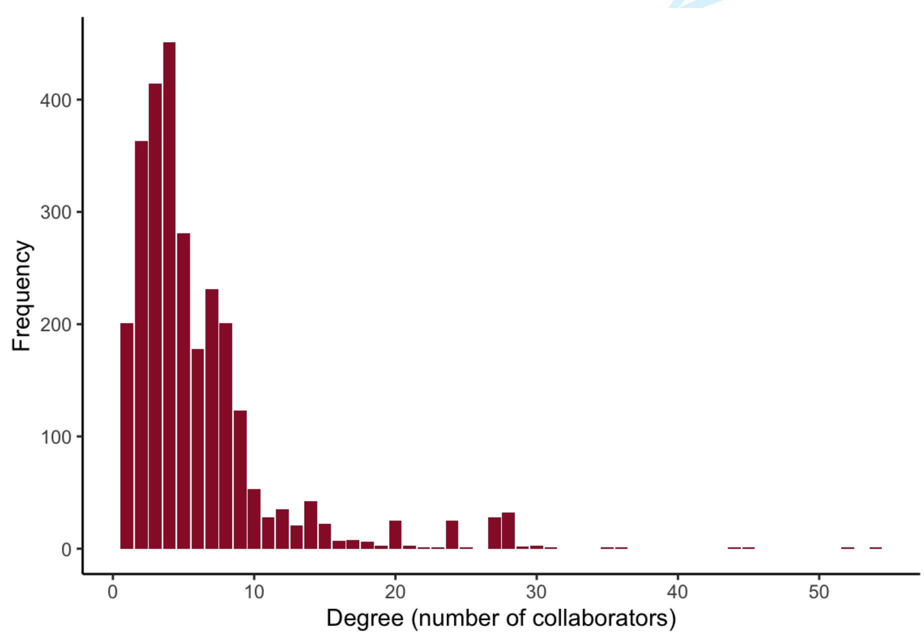
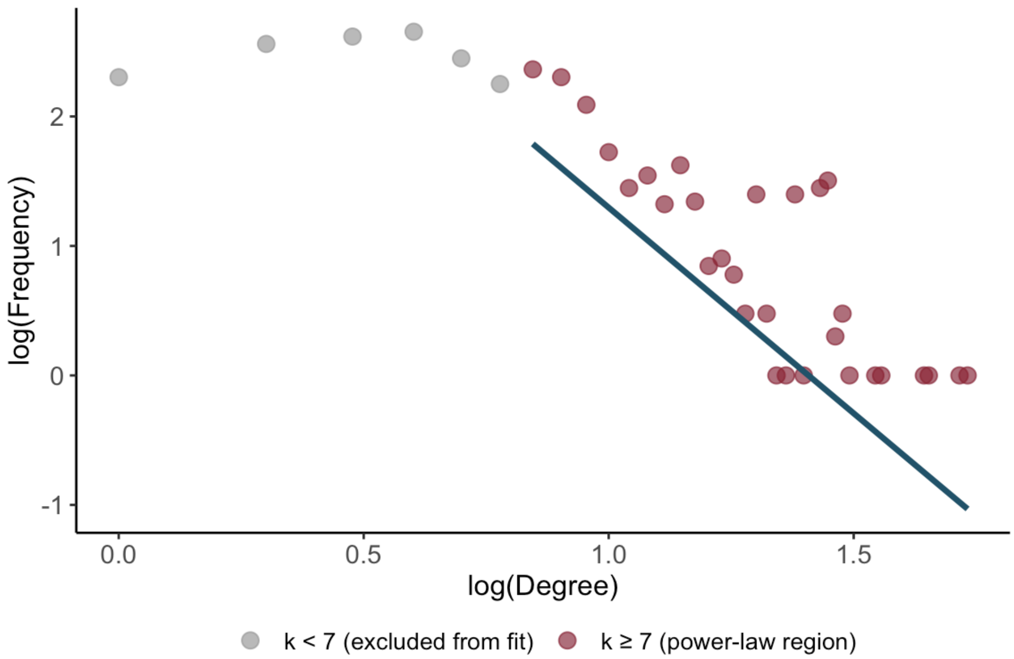


Figure 3. *Log-log degree distribution of authors in the unweighted network (scale-free test).*



Notes: Degrees above the threshold (dark red) follow the fitted power law (blue line), while lower degrees (gray) deviate from this pattern.

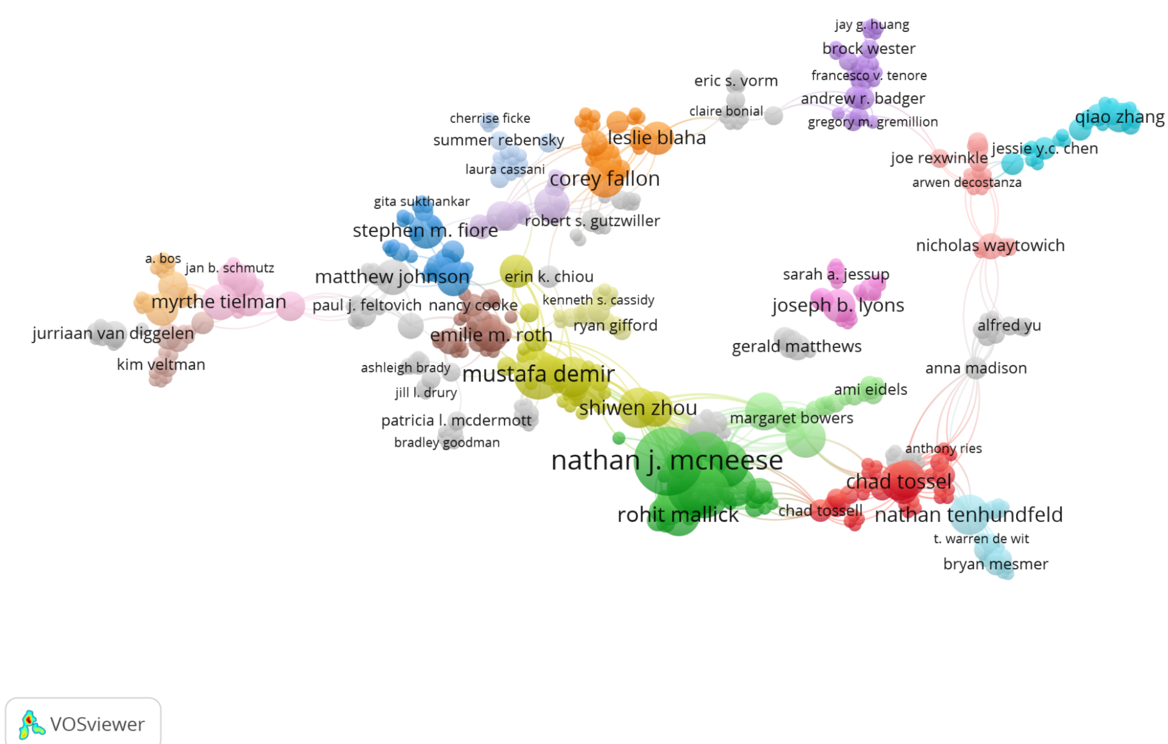
Finally, we examined the “giant component” (GC) of 540 connected authors (Table 2, Figure 4). While density increases tenfold from the full network and the average degree rises to 9.02 collaborators, the GC still exhibits poor integration. The average path length and diameter suggest substantial internal fragmentation, with some authors requiring 15 steps to reach one another despite being in the same connected component. Additionally, the slight drop in transitivity suggests that the 474 smaller components are where the small, tightly-knit teams (triangles) exist, rather than within the GC. Rather than functioning as an integrated community where knowledge on human-AI teams is most efficiently shared, the GC itself appears fragmented into loosely connected subcommunities with limited direct collaborations.

Table 2. *Network properties for giant component of the whole network.*

nodes	edges	density	avg_degree	avg_path_length	diameter	transitivity
540	2435	0.02	9.02	5.45	15	0.67

Notes: density = measure (scale of 0 to 1) of how interconnected the GC is; avg_degree = average degree an author in the GC has; avg_path_length = average number of collaborations needed to connect any two authors in the GC; diameter = longest shortest path between any two nodes in the GC; transitivity = measure (scale of 0 to 1) of overall tendency for the GC's nodes to form triangles.

Figure 4. *Visualization of authors in the GC, weighted by publication count.*



Note: VOSViewer positions nodes to indicate their relatedness and identified clusters within the GC, which are color-coded. A more detailed discussion on the clustering technique is provided by Van Eck et al. (2010). By default, our visualizations use document counts as node weights, with a resolution value set to 1.00. Additionally, we selected full counting in VOSViewer to maintain consistency with our R-based analysis.

To help put these findings into context, we compared the key network metrics from human-AI research to those in established scientific fields (Ye et al., 2013). The low average papers per author is unsurprising given the novelty of human-AI research. However, this is potentially due to the prevalence of small authorship teams not in the GC, similar to the trend mentioned in tourism and hospitality by Ye et al. (2013). Of note, the percentage of the main component is strikingly low, consistent with the highly fragmented structure of the network in human-AI teams research. At the same time, the exceptionally high transitivity suggests that researchers form tight collaborative circles within their local networks, but these circles remain disconnected from one another. Overall, the human-AI teams field appears to be at an earlier stage of network development (especially compared to more established fields such as biomedicine and physics), characterized by multiple independent research silos rather than an integrated scientific community.

Table 3. *Comparison of our network metrics to metrics in other fields.*

Metric	**Tourism & Hospitality**	**Biomedical Research**	**High-Energy Physics**	**Computer Science**	***Human-AI Teams***
Average papers per author	1.1	6.4	11.6	2.6	1.4
Average authors per paper	1.87	3.75	8.96	2.22	4.06
Average collaborations per author	2.58	18.10	173.00	3.59	5.93
Percentage of authors in the GC	59.30%	92.60%	88.70%	57.20%	18.88%
Average path length in the GC	7.2	4.6	4.0	9.7	5.5
Diameter of the GC	19	24	19	31	15
Transitivity (AKA clustering coefficient)	0.75	0.07	0.73	0.50	0.82

Notes: Metrics from other fields were obtained from Ye et al. (2013), Table 3.

Lastly, we examined specific authors within the GC. Figure 5 shows the top 20 authors by number of publications, with a noteworthy pattern that many share a common institution (Clemson and Arizona State). We then calculated betweenness centrality for all 540 authors in the GC; the overall average was 0.0083 (range from 0 to 0.35), indicating that on average, authors appear in less than 1% of all shortest paths in the GC. Table 4 presents the top 10 bridge authors, revealing extreme concentration of bridging capacity among the authors who are also the most prolific in terms of number of publications and have the highest degree. This concentration of “bridging” within a few top authors suggests that the field’s limited connectivity depends heavily on these top authors. If these top bridges reduce their collaborative activity or leave the field, substantial portions of the giant component could fragment into isolated clusters, further exacerbating the network’s already severe fragmentation.

Figure 5. *Top 20 authors by number of publications.*

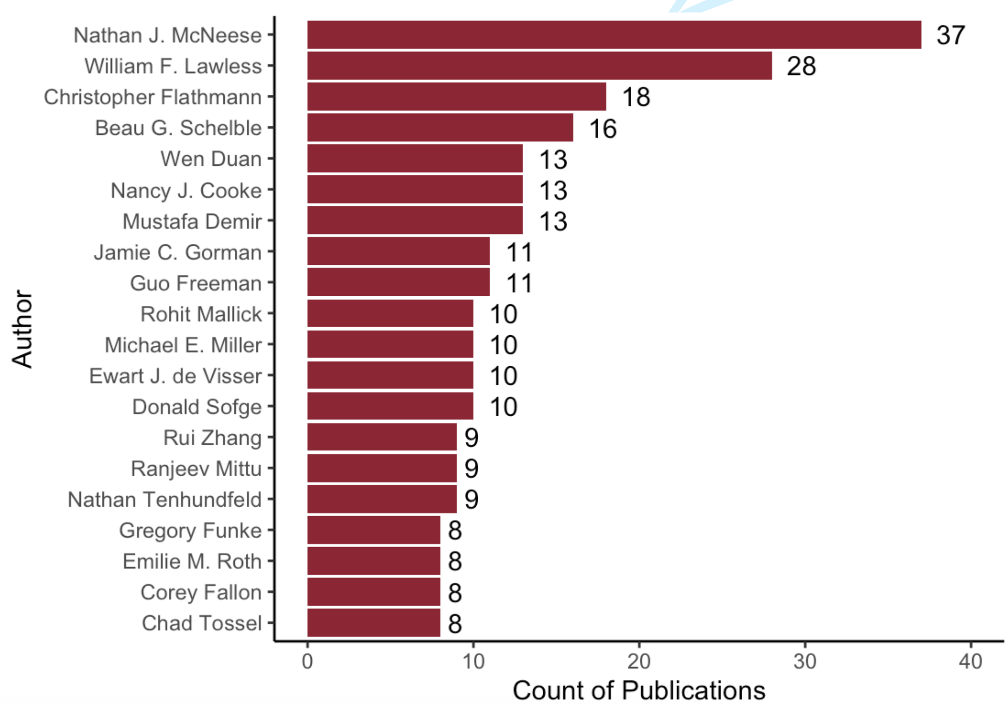


Table 4. *Top 10 authors with highest betweenness score.*

Author	Publications	Degree	Betweenness
Nathan J. McNeese	37	52	0.35
Ewart J. de Visser	10	45	0.24
Emilie M. Roth	8	54	0.20
Catholijn Jonker	5	11	0.18
Anna Madison	3	17	0.17
Robert Hoffman	5	44	0.15
Nicholas Waytowich	4	27	0.15
Leslie Blaha	6	24	0.15
Erin K. Chiou	3	14	0.15
Matthew Johnson	7	20	0.14

Predictive Analyses (RQ2)

A series of ERGMs were conducted to investigate the degree to which the following author attributes and network elements predicted the presence of a tie (i.e., collaboration between authors): author productivity in terms of number of publications, difference in number of publications between two potential collaborators, author degree centralization (i.e., authors with more ties), triangles (i.e., transitivity), and homophily by author affiliation and primary subject area. Analyses followed guidelines from Handcock et al. (2025) and the *ergm* package in R. First, a baseline empty model was fit (B = -4.85, $p < 0.001$); the result aligned with the low density from descriptive analyses, such that the empty model with no predictors suggested only a 0.8% chance of any two authors collaborating. Each predictor was then tested in a separate ERGM (results shown in Table 5). Finally, a full ERGM was fit with all significant predictors from Table 5; the results of the full ERGM are shown in Table 6. The results showed moderate evidence of preferential attachment (authors with more publications and more existing collaborations were more likely to get collaborations), substantial evidence of homophily (authors more likely to collaborate based on match in publication count, affiliation, and subject area), and inconclusive evidence of transitivity.

Table 5. *Results from separate ERGMs for each predictor (2025 data).*

Theory	Predictor	Estimate (SE)	Odds	Interpretation
Preferential attachment	Author total publications	0.04 (0.00) **	1.04	Authors with more publications were slightly more likely to collaborate
Preferential attachment	Author 2025 publications	0.30 (0.02) **	1.35	Authors with more publications in 2025 were more likely to collaborate
Homophily	Author match in total publications	0.01 (0.01)	1.01	Not significant
Homophily	Author match in 2025 publications	0.20 (0.02) **	1.22	Prolific authors tend to collaborate with less prolific authors
Preferential attachment + homophily	Author total publications AND Author match in total publications[3]	Total: 0.26 (0.01) ** Match: -0.28 (0.01) **	Total: 1.30 Match: 0.75	Authors with similar total publications are more likely to collaborate, after controlling for overall author productivity
Preferential attachment	Author degree centralization	-1.74 (0.15) **	0.18	Authors with more collaborations are less likely to add additional collaborators
Transitivity	Completion of triangles in network	N/A	N/A	Did not converge
Homophily	Author match in affiliation	7.72 (0.07) **	2242.24	Authors from the same institution are extremely more likely to collaborate

[3] Although author match was not significant when tested individually, it was significant when tested alongside author total publications. This is similar to the effect seen in income networks: without controlling for wealth, richer-poorer interactions might seem more common (positive effect) if richer people are more spread out in the network. Likewise, more prolific authors initially seemed more likely to collaborate with less prolific authors, but after controlling for overall number of publications, the effect reversed.

Theory	Predictor	Estimate (SE)	Odds	Interpretation
Homophily	Author match in subject area	4.85 (0.08) **	127.21	Authors primarily in the same subject area are extremely more likely to collaborate

* $p < 0.05$, ** $p < 0.01$

Table 6. *Results from combined ERGM for all significant predictors (2025 data).*

Predictor	Estimate (SE)	Exp(Est.)	Interpretation
edges (baseline)	-9.66 (0.13) **	< 0.001	Any pair of two authors has <0.1% chance of collaboration
author total publications	0.29 (0.02) **	1.33	Each additional publication that an author has increased the odds of collaboration by about 33%
author match in total publications	-0.19 (0.02) **	0.83	Every one-unit increase in the *difference* in number of publications between two authors leads to a *reduction* in the odds of collaboration
author degree centralization	0.83 (0.34) *	2.29	Authors with many existing collaborators (high degree) are slightly more likely to form new collaborations
author match in affiliation	6.87 (0.09) **	966.51	Collaborations are 967x more likely when authors share the same institutional affiliation
author match in subject area	4.25 (0.11) **	70.18	Collaborations are 70x more likely when authors share the same subject area

* $p < 0.05$, ** $p < 0.01$

Temporal Analysis (RQ3)

Filtering our database of authors to those who have published in 2022 yields 442 authors with 29 forming the main giant component. In 2025, the number grew to 779 authors with a slightly larger main component of 34 authors. Figure 6 shows two loosely connected subgroups in 2022, with a few authors acting as bridges between them. There are not many sub-communities within these two main groups. By contrast, 2025 has a much larger giant component with many subclusters, each with stronger internal ties. The clusters are denser and many nodes are easily reachable from one another. Although the 2025 network shows increased interconnectedness, likely due to the expansion of the field, it simultaneously displays stronger local clustering (Figure 7).

Figure 6. *Visualization in VOSViewer of GC from 2022.*

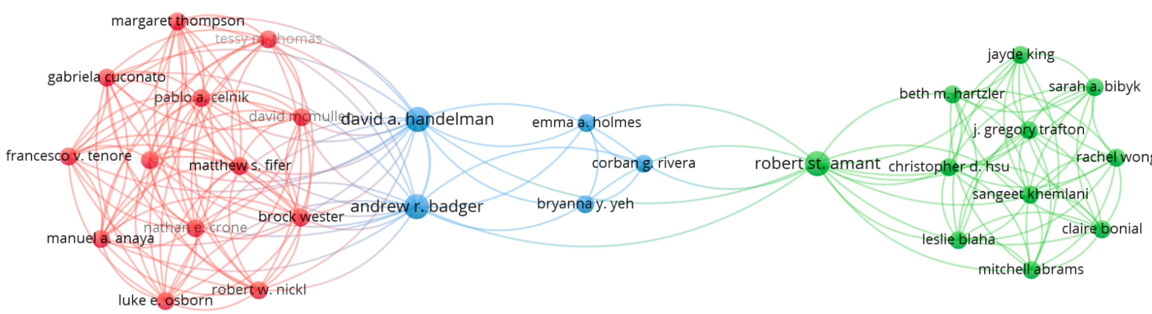
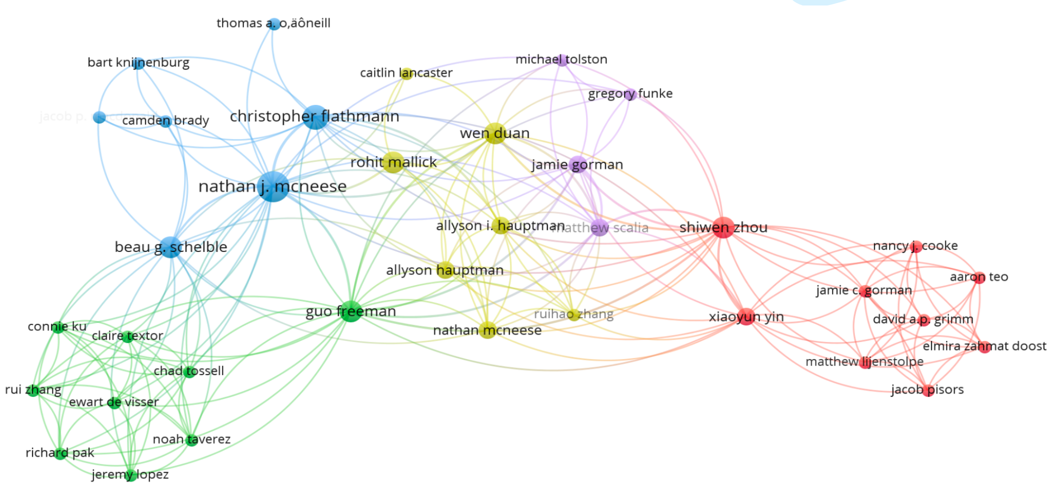


Figure 7. *Visualization in VOSViewer of GC from 2025.*



Looking at Table 7, there is clear growth in terms of number of researchers and collaboration, but at the same time, increasing fragmentation with more disconnected components and isolates (along with a proportionally smaller GC). Density declined slightly (i.e., a sparser network), but interestingly, it increased within the GC. This, coupled with the slightly shorter path length and increase in degree within the GC suggests that the researchers in the GC are collaborating more intensively, while still disconnected from a growing periphery of authors outside of the GC.

Table 7. *Comparison of network metrics from 2022 network to 2025 network.*

	in the whole network…		**in the GC…**	
Metric	**2022**	**2025**	**2022**	**2025**
Nodes	442	779	29	34
Edges	1108	2238	102	180
Isolates	15	20	N/A	N/A
Components	94	159	N/A	N/A
Density	0.011	0.007	0.251	0.321
Average Degree	5.01	5.75	7.03	10.59
Transitivity	0.91	0.93	0.73	0.68
Average Path Length	N/A	N/A	2.07	1.84
Diameter	N/A	N/A	3	3

Finally, we re-ran the same ERGMs from RQ2 on the 2022 data. Results are shown in Table 8. There were several notable differences when compared to the final model from 2025. First, the network was much less sparse than in 2025, and author degree centralization was significant but in the opposite direction, such that there were moderate diminishing returns to additional collaborators back in 2025. In other words, preferential attachment was not present in 2022 but moderately present in 2025. Second, interestingly, the homophily effect by affiliation and subject area showed drastic differences: authors tended to collaborate *across* different institutions in 2022, but that effect shifted to an extremely strong preference for same-institution collaborations in 2025. The homophily effect by subject area was still present in 2022, but it was much weaker. Finally, the effects of total publications and match in number of publications remained roughly consistent between years.

Table 8. *Results from combined ERGM for all significant predictors (2022 data).*

Predictor	**Estimate (SE)**	**Exp(Est.)**	**Interpretation**
edges (baseline)	-4.93 (0.11) **	0.007	Any pair of two authors has a 0.7% chance of collaboration
author total publications	0.29 (0.03) **	1.33	Each additional publication that an author has increased the odds of collaboration by about 33%
author match in total publications	-0.27 (0.04) **	0.76	Every one-unit increase in the *difference* in number of publications between two authors leads to a *reduction* in the odds of collaboration
author degree centralization	-0.91 (0.24) **	0.40	Authors with many existing collaborators (high degree) are somewhat *less* likely to form new collaborations

author match in affiliation	-1.27 (0.64) *	0.28	Collaborations are 72% *less* likely when authors share the same institutional affiliation
author match in subject area	1.27 (0.64) *	3.55	Collaborations are 3.55x more likely when authors share the same institutional affiliation

* $p < 0.05$, ** $p < 0.01$

Note: As with 2025, the ERGM testing triangles did not converge.

Discussion

In sum, our analyses on human-AI teaming research from 2003 to 2025 reveals a severely fragmented coauthorship network characterized by isolated silos, sparse connections, and a relatively small giant component of super-collaborators. These results are uniquely fragmented compared to established fields (e.g., biomedicine and physics), and critical network vulnerability exists in a few key dominant authors who are “bridges” between clusters of authors. The ERGM results likewise show substantial homophily and preferential attachment effects favoring same-institution, same-field, and already-productive authors for collaboration. Finally, a comparison of the network from 2022 to 2025 reveals accelerating fragmentation and consolidation into institutional silos rather than maturation towards an integrated field.

Our study has enormous implications for understanding the future of psychology in 2125. The topic of human-AI teams should represent the future of psychological research — integrating what we know about human psychology with AI ethics, algorithmic decision-making, and more — yet the analyses show that research is *increasingly* fragmented, rather than trending towards integration. While it is certainly not feasible to expect a high density network where all authors are collaborating with one another, the lack of any global paths and high vulnerability of structural holes due to betweenness centralized in a few prolific authors suggests that knowledge is trapped and fails to efficiently flow between scholars. Put differently, if McNeese in particular were to exit the network, research on human-AI teams would become even more isolated and fragmented with few if any weak ties, small world effects, and other network attributes necessary for an efficient and effective collaboration network. Furthermore, the strong evidence of increasing homophily, especially with regard to institutional affiliation, suggests that the field is actively moving *away* from integration, creating potential for alarming echo chambers and silos of researchers. Put together, all of this makes for a bleak picture of 2125 if the collaboration network continues along this trajectory.

This paper points towards several future initiatives that must be considered if we are to have a more integrated, open field of psychological research — which also be tested in future studies. First, the collaboration network can embrace recent cultural shifts towards open science and big team science research (Vazire, 2018). Shared data and materials, and support for diverse collaborations especially among early career researchers, can all help reduce the barriers to integrated networks and lower the walls surrounding existing research silos. Second, structural interventions should be tested for their efficacy in improving the network. For example, funders could promote or even require cross-institutional, cross-disciplinary teams; journals could seek to publish more interdisciplinary work, and tenure committees could explicitly value bridging alongside productivity in their evaluations. Lastly, the growth in technology-mediated collaboration solutions, such as AI-powered matchmaking or digital platforms to facilitate virtual collaborations, could help encourage and stimulate further boundary-spanning in networks.

Briefly, the present study's limitations are primarily in its focus on human-AI teams research and limited application of temporal analyses. We argue that this study is a proof-ofconcept that can easily be applied to explore other topics within psychological research. Although human-AI teams is a relevant research area, other fields of study should be investigated as well — however, we note that bibliometric studies commonly focus on smaller subsets of networks, as larger networks (e.g., *all* research in psychology) create computational challenges for both visualization and ERGMs. Additionally, we relied on a static comparison of 2022 to 2025 networks to show change over time. More advanced longitudinal and simulation-based network analyses (see Maupin et al., 2023 for an overview) could be applied to more thoroughly examine change in the network and simulate potential future changes.

We hope that the present paper serves to show, empirically, that the field of psychological science research is fragmented (through a case study example of human-AI teams) and trending in the wrong direction when looking ahead to 2125. By calling attention to this, we seek to encourage future researchers to (a) apply these methods to examine the collaboration networks of other fields of inquiry, and (b) engage in a "network-aware meta-science" whereby researchers are incentivized to and support in their pursuit of interdisciplinary research, integrated collaboration, and effective knowledge distribution.

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