Title: Trends in self-citation rates in neuroscience literature

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Abstract

Citation metrics influence academic reputation and career trajectories. Recent works have highlighted flaws in citation practices in the neurosciences, such as the under-citation of women. However, self-citation rates—or how much authors cite themselves—have not yet been comprehensively investigated in the neurosciences. This work characterizes self-citation rates in basic, translational, and clinical neuroscience literature by collating 157,001 articles from 63 journals between the years 2000-2020. In analyzing over eight million citations, we demonstrate four key findings: 1) self-citation rates over the years are constant for the Last Authors but decreasing for the First Authors, 2) self-citation rate is strongly correlated with years of academic experience, 3) authors from particular countries cite themselves much more than other countries, and 4) early-career men cite themselves 41% more than early-career women. As it is essential for authors to be aware of their self-citation practices, we developed a tool to calculate self-citation rates: https://github.com/mattrosenblatt7/self_citation. Our characterization of self-citation practices represents an initial step towards improving equity in citations and, ultimately, neuroscience research.

1. Introduction

As quantitative publication metrics are increasingly used as a proxy for productivity and performance in academia, meta-science citation research has unveiled troubling citation trends, including an establishment of unfounded authority through citation distortions [1] and false inflation of impact factors by specific journals [2]. Since citations and other factors like the h-index are critical for hiring and promotion in an increasingly tenuous academic job market [3,4], it is essential to examine citation practices. Citations are also used as a proxy for how well a researcher disseminates their work, which is both important for spreading knowledge and establishing a scientific reputation, thus influencing career trajectories. Citation inequality has

been explored across various fields [5]. Recent examination in the neuroscience literature revealed both racial and gender biases with the under-citation of racial and ethnic minority groups [6] and women [7–9]. Since citation metrics have widespread effects on various academic milestones, including hiring, promotions, and reputation [10,11], identifying and addressing potenitally discriminatory citation practices is central to ensuring the integrity of these activities.

One component of citation bias that remains understudied in the neuroscience literature is self-citation, or how much authors cite themselves. Self-citation can be calculated from two different perspectives: 1) on an "author level" as the proportion of an author's total citations that come from their work [12,13], or 2) on an "article level" as the proportion of a single article's references on which the citing author is also an author [14]. Since the former accounts for the total number of times an author cites themselves (across all papers) divided by the total number of citations the author has received, it helps identify when a particular author only accumulates citations from themselves. However, in this manuscript, we defined self-citation as the latter for two main reasons. First, we believe it reflects one's intention to cite themselves more closely, as one cannot control how much others cite their works. Second, viewing self-citations at the article level is more actionable for authors and journals at the time of submission. Crucially, studies have found h-index manipulation through self-citation [15] and less self-citation by women compared to men [7,16]. Given the previously discovered self-citation bias in certain groups [7,16] and the potential downstream effects of self-citations [17], a comprehensive analysis of self-citation rates in neurology, neuroscience, and psychiatry literature is needed.

This work summarizes self-citation rates in neurology, neuroscience, and psychiatry literature across the last 21 years, 63 journals, 157,001 articles, and 8,270,200 citations. We then build upon these calculations by exploring trends in self-citation over time, by seniority, by country, by gender, and by different subfields of research. Finally, we discuss the implications of our findings in the broader academic landscape and share a tool for authors to calculate their self-citation rates: https://github.com/mattrosenblatt7/self_citation.

2. Results

2.1 Data

We downloaded citation information from 157,001 papers from Scopus across 63 different journals representing the top neurology, neuroscience, and psychiatry journals based on impact factor (Table S1) from 2000-2020. These 157,001 papers included a total of 8,270,200 citations.

2.2 Metrics

Using the Scopus database and Pybliometrics API [18], we calculated three metrics for each individual paper: First Author self-citation rate, Last Author self-citation rate, and Any Author self-citation rate, where self-citation rate is defined as the proportion of cited papers on which the citing author is also an author. As an example, consider a hypothetical paper by Author A, Author B, and Author C that cites 100 references.

- If Author A is an author on 5 of those references, then the First Author self-citation rate is 5/100=5%.
- If Author C is an author on 10 of those references, then the Last Author self-citation rate is 10/100=10%.
- If at least one of Author A, Author B, OR Author C is an author on 18 of the references, then the Any Author self-citation rate is 18%.

We will use the above definitions of self-citation throughout the paper because we believe that these most reflect one's intention to cite themselves. Furthermore, our estimations via Python code of the above three metrics showed strong agreement with 906 manually scored articles from a subset of psychiatry journals (*r*'s>0.9) (Figure S1).

We performed 1,000 iterations of bootstrap resampling on the article level (i.e., resample articles with replacement) to obtain confidence intervals for all analyses. We additionally performed 10,000 iterations of permutation testing to obtain P values for all significance tests. All P values are reported after applying the Bonferroni correction, unless otherwise specified.

2.3 Self-citation rates in 2016-2020

In the last five years of our dataset (2016-2020), the overall self-citation rates were 4.50% (95% CI: 4.44%, 4.56%) for First Authors, 7.95% (95% CI: 7.89%, 8.02%) for Last Authors, and 14.42% (95% CI: 14.30%, 14.53%) for Any Authors (Table 1). In all fields, the Last Author self-citation rates were significantly higher than that of First Author self-citation rates (P's<0.004). Neuroscience had a significantly lower self-citation rate than neurology and psychiatry for First, Last, and Any Authors (P's<0.004). We found a significantly lower First Author self-citation rate for neurology compared to psychiatry (P=0.004), and significantly higher Last Author and Any Author self-citation rates for neurology compared to psychiatry (P's<0.004).

Field	First Author	Last Author	Any Author
Overall	4.50 (4.44, 4.56)	7.95 (7.89, 8.02)	14.42 (14.30, 14.53)
Neurology	4.90 (4.80, 5.00)	9.06 (8.94, 9.18)	17.37 (17.17, 17.57)
Neuroscience	3.52 (3.43, 3.62)	6.60 (6.48, 6.70)	10.65 (10.48, 10.80)
Psychiatry	5.28 (5.18, 5.37)	8.42 (8.30, 8.53)	15.85 (15.69, 16.02)

Table 1. Self-citation rates in 2016-2020 for First, Last, and Any Authors broken down by field (neurology, neuroscience, psychiatry).

2.4 Temporal trends in self-citation rates

Furthermore, self-citation rates have changed since 2000 (Figure 1). For example, First Author self-citation rates were 6.53% (95% CI: 6.34%, 6.75%) in 2000 and 4.18% (95% CI: 4.07%, 4.29%) in 2020. First Author self-citation rates decreased at a rate of -1.05% per decade (95% CI: -1.11%, -1.00%), Last Author self-citation rates increased at a rate of 0.02% per decade (95% CI: -0.05%, 0.09%), and Any Author self-citation rates increased at a rate of 0.54% per decade (95% CI: 0.43%, 0.64%). Corrected and uncorrected P values for the slopes are available in Table S4. Further details about yearly trends in self-citation rate by field are presented in Figure S2.

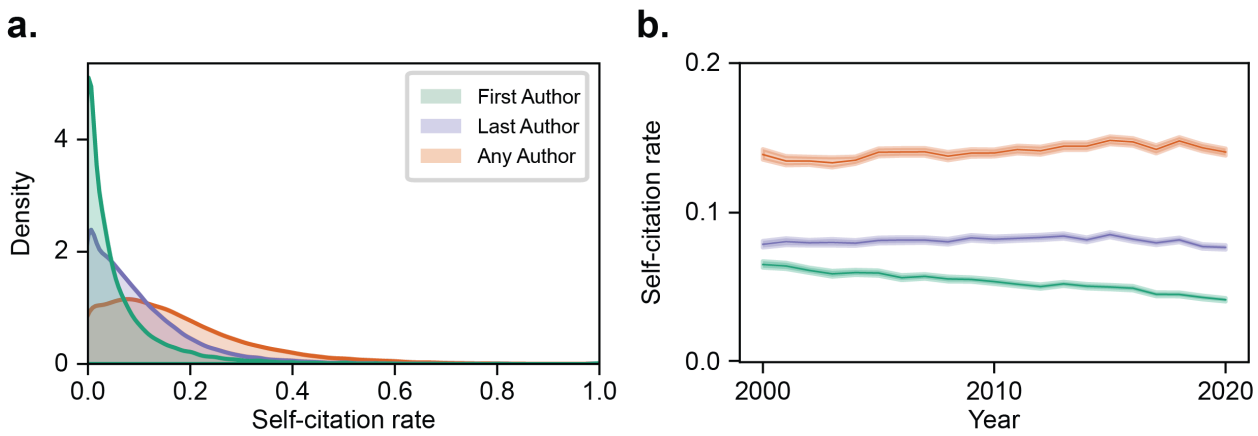

Figure 1. Self-citation rates **a)** in the last five years and **b)** since 2000. **a)** Kernel density estimate of the distribution of First Author, Last Author, and Any Author self-citation rates. **b)** Average self-citation rates over every year since 2000, with 95% confidence intervals calculated by bootstrap resampling.

2.5 Author seniority and self-citation rate

We also considered that the self-citation rate might be related to seniority. To test this, we calculated each author's “academic age” as the years between the publication of their first paper (in any author position) and their current paper. For example, if the Last Author of a 2017 paper published their first paper in 1995, their academic age would be 22. We averaged the self-citation rates across each academic age, only including those ages with at least 50 papers in the dataset, and found marked increases in self-citation rate with greater academic age (Figure 2a). For instance, at ten years, the self-citation rate for First Authors is about 5%, while this number jumps to over 10% at 30 years. Academic age appears to be a more robust indicator of self-citation than authorship position, as, for a given academic age, First Author and Last Author self-citation rates are comparable (Figure 2b).

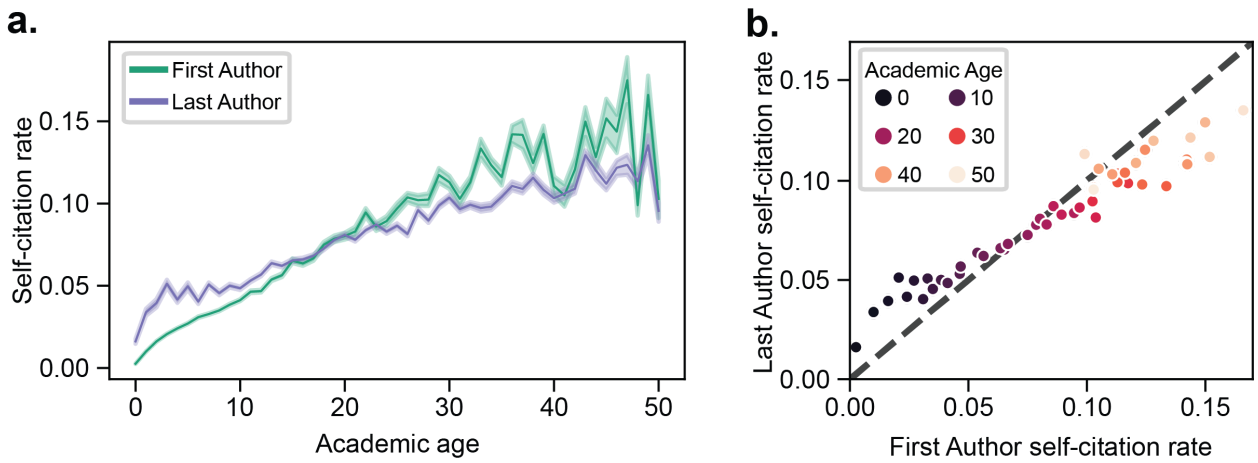

Figure 2. Average self-citation rates for each academic age in years 2016-2020. **a)** Self-citation rate vs. academic age for both First and Last Authors. Shaded regions show 95% confidence intervals obtained via bootstrap resampling. **b)** Comparison of self-citation rates by academic age for First and Last Authors. For a given academic age, a single point is plotted as (x=First Author self-citation rate for authors of academic age *a*, y=Last Author self-citation rate for authors of academic age *a*). The dashed line represents the y=x line, and the coloring of the points from dark to light represents increasing academic age.

2.6 Geographic location and self-citation rate

In addition, we used the country of the affiliated institution of each author to determine the self-citation rate by institution country over the last five years (2016-2020). We averaged First Author and Last Author self-citation rates by country and only included countries with at least 50 papers. This analysis is distinct from country self-citation rate because we calculated self-citation at the level of the author, then averaged across countries. In contrast, previous studies have operationalized country self-citation rates as when authors from one country cite other authors from the same country [19]. The results are shown on a map of the world using GeoPandas [20] (Figure 3; see Methods) and also presented in table format (Table S3). Self-citation rates in the highest self-citing countries were nearly double that of the lowest for the First and Last Authors. For instance, the First Author self-citation rate in the United States is 4.73%, while in China, it is 2.41%.

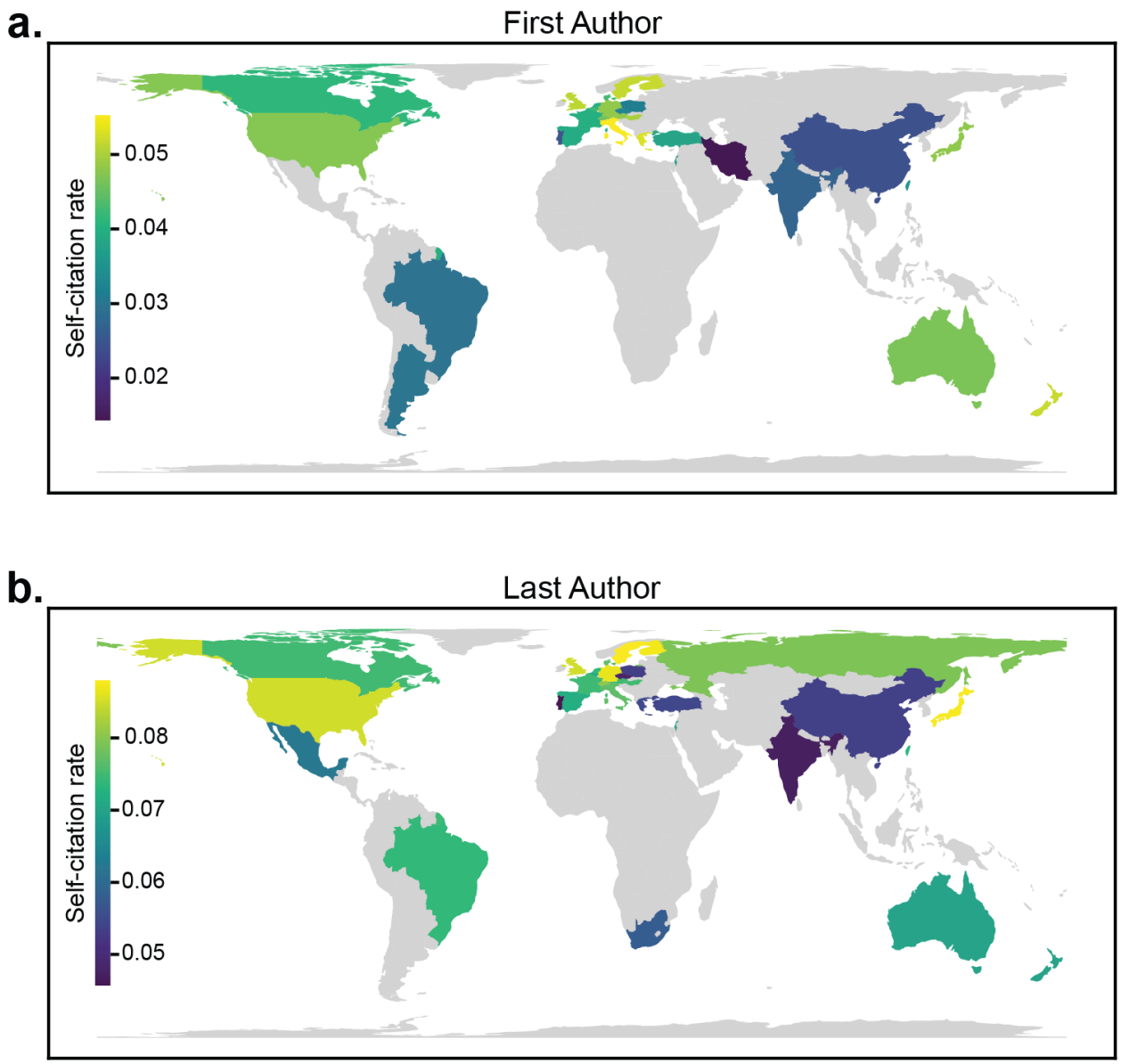

Figure 3. Self-citation rates by country for **a)** first and **b)** Last Authors from 2016-2020. Only countries with >50 papers were included in the analysis. Country was determined by the affiliation of the author.

2.7 Gender disparities in self-citation

Gender disparities are pervasive in academia, including in authorship and citation practices. As such, we investigated the differences in self-citation by gender. For each paper, we assigned a probability of a particular name belonging to a woman or a man using the Genderize.io API. We retained only authors with >80% probabilities. There are clear limitations to these types of packages, as described in [7], because they assume genders are binary and do not account for authors who identify as nonbinary, transgender, or intersex. As such, the terms “women” and “men” indicate the probability of names being that gender as opposed to a specific author

identifying as a man or woman. Despite these limitations, we believe these tools can still help broadly uncover gender differences in self-citation rates.

We calculated the proportion of men and women First and Last Authors since 2000 (Figure 4a). Although the authorship proportions have begun to converge to be equal by gender, the gender disparity among the Last Authors was more notable than among the First Authors. Based on linear fits, we estimated that men and women would be equally represented as First and Last Authors in 2025 (95% CI: 2024, 2026) and 2052 (95% CI: 2050, 2054), respectively.

In 2020, there were significant differences between First Author self-citation rates of men and women (P<0.004). First authors who were men had average self-citation rates of 5.12% (95% CI: 4.93%, 5.31%), while women authors had average self-citation rates of 3.34% (95%CI: 3.19%, 3.49%), which is significantly different (P<0.004). Similarly, in 2020, Last Authors who were men had significantly higher self-citation rates than those who were women (P<0.004), with self-citation rates of 8.18% (95%CI: 7.99%, 8.36%) and 6.80% (95% CI: 6.56%, 7.04%), respectively.

In addition, men persistently had higher self-citation rates than women since 2000 (Figure 4b), though the gap has slowly decreased. Linear fits were used to estimate that self-citation rates for men and women would be equal for First Authors in the year 2105 (95% CI: 2071, 2171) and equal for the Last Authors in 2053 (95% CI: 2041, 2072). Furthermore, we calculated the ratio of men to women self-citations over the past two decades (Figure 4c). For First Authors, men have consistently cited themselves more than women by 42.5-67.8% depending on the year. Among Last Authors, there was a steep decrease in 2002, but since then, men have cited themselves 17.8-36.5% more than women.

Seniority may account for gender differences in self-citation rate, as there are gender disparities in faculty positions and ranks [21–24]. To explore the effect of seniority, we investigated self-citation rates by academic age and gender (2016-2020). Gender disparities for the same academic age emerged early in an academic career and were relatively persistent throughout most of the career (Figure 4d-e). For instance, in the previous five years (2016-2020), there were 12,558 papers by early-career women authors and 14,574 by early-career men authors. Women authors had 781,096 references and 17,836 self-citations (2.28% self-citation rate), while men authors had 884,331 references and 28,560 self-citations (3.23% self-citation rate). This equated to a 41.4% higher self-citation rate for men than women during the first ten years of their careers (P<0.004).

We considered two factors that might contribute to the gender discrepancy in self-citation rate by academic age: the number of papers published for authors of a given academic age and the self-citation rate for a given number of papers. We compared the number of papers for men and women at a given academic age (Figure 5f-g) and found that men had a higher number of papers. This trend started early in the career (academic age<=10 years), where men had significantly more papers than women (P<0.004). For example, at an academic age of 10 years, men were authors on an average of 44 papers, and women authored 30 papers on average. In

addition, we divided the number of papers into groups (Figure S3) and computed self-citation rate by gender for each group. Men had significantly higher self-citation rates for 0-9 papers (P<0.004), 10-19 papers (P=0.0111), 20-29 papers (P=0.0185), and 40-49 (P<0.004) papers. All other differences were not statistically significant.

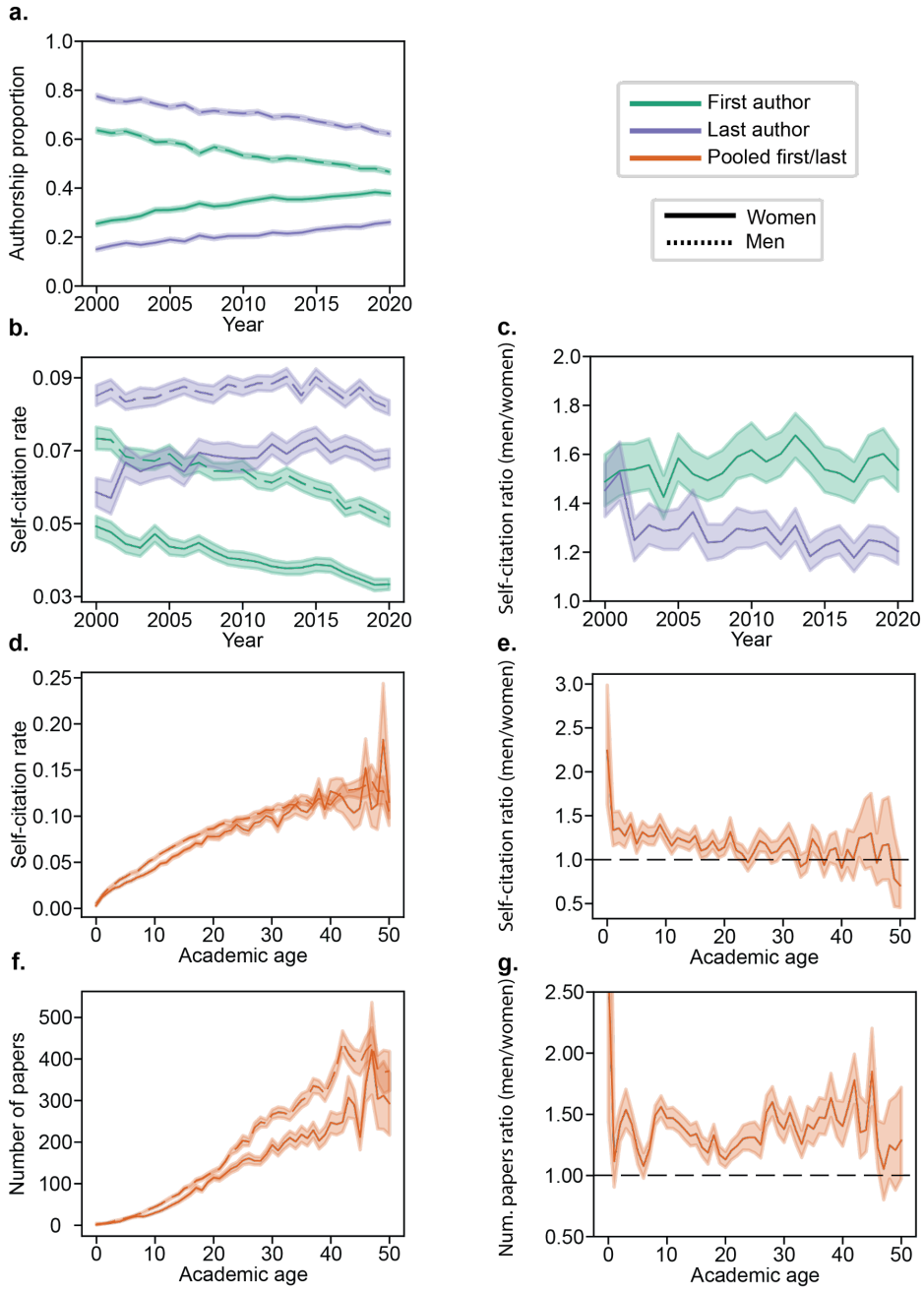

Figure 4. Gender disparities in authorship and self-citation. **a)** Proportion of papers written by men and women First and Last Authors since 2000. **b)** Average self-citation rates for men and women First and Last Authors. **c)** Ratio of average self-citation rates of men to women for First and Last Authors. **d)** Self-citation rates by academic age for men and women authors, where the dashed line represents men and the solid line women. **e)** Ratio of self-citation rates of men to women by academic age. **f)** Number of papers by academic age for men and women, where the dashed line represents men and the solid line women. **g)** Ratio of average number of papers of men to women by academic age. In all subplots, 95% confidence intervals of the mean were calculated with 1000 iterations of bootstrap resampling.

2.8 Self-citation rates by subtopic

We next investigated how self-citation rate varies within subfields of neuroscience research. Based on Scopus abstract data for papers from 2016-2020, we developed a topic model using latent Dirichlet allocation (LDA). In LDA, each abstract is modeled as a distribution of topics, and each topic contains probabilities for many different words.

We assigned each paper to the topic with the highest probability to determine "subtopics" for each paper. The topic number was chosen as 13 with a parameter search (Figure S4), and results with seven topics are also presented in the SI (Figures S6-7). Based on the most common words of each topic (Figure S5), we assigned 13 overall themes: 1) Aging & development, 2) Animal models, 3) Cellular, 4) Clinical research, 5) Clinical trials, 6) Dementia, 7) Depression & anxiety, 8) Functional imaging, 9) Mechanistic, 10) Pain, 11) Schizophrenia, 12) Social neuroscience, 13) Stroke. We then computed self-citation rates for each of these topics (Figure 5).

We generally found that clinical trial research had the highest self-citation rates for First Authors at 7.34% (95% CI: 7.22%, 7.44%), whereas animal research had the lowest self-citation rate at 3.32% (95% CI: 3.28%, 3.36%). For Last Authors, self-citation rates were highest for Dementia research at 10.78% (95% CI: 10.67%, 10.89%) while Social neuroscience had the lowest self-citation rate at 5.85% (95% CI: 5.79%, 5.90%). For Any Author, Clinical trials once again had the highest self-citation rate at 22.37% (95% CI: 22.19%, 22.55%), and Social neuroscience had the lowest self-citation rate at 10.03% (95%CI: 9.94%, 10.11%). One possible explanation for the differing self-citation rates by field is a different number of authors per paper, so we correlated the number of authors per paper in a given field with self-citation rate (Spearman's r=0.1484, 0.6648, 0.7747 for First Author, Last Author, and Any Author self-citation rates, respectively; corrected and uncorrected P values are available in Table S4).

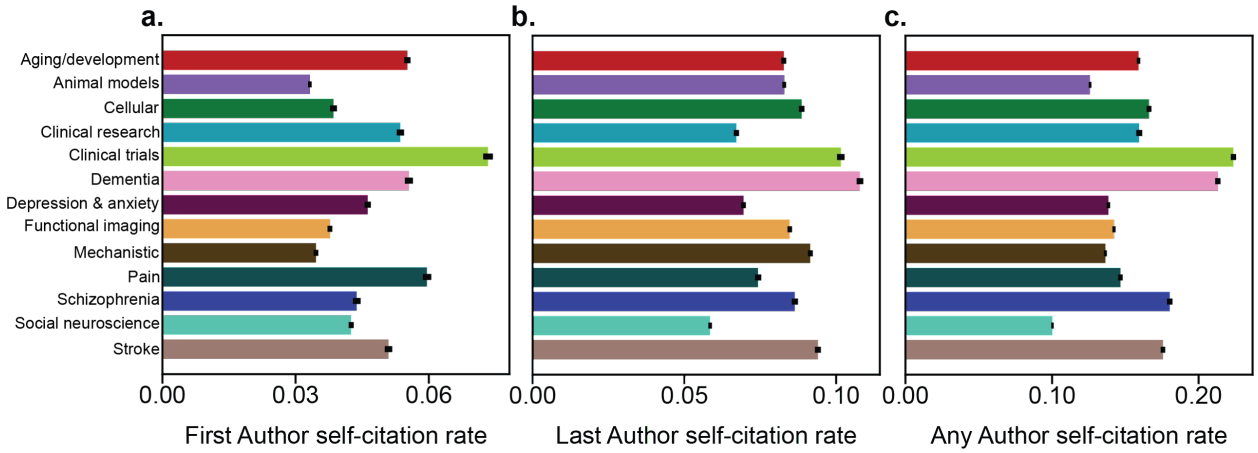

Figure 5. Self-citation rates by topic for First, Last, and Any Authors. Topics were determined by Latent Dirichlet Allocation. Confidence intervals of the average self-citation rate are shown based on 1000 iterations of bootstrap resampling.

2.9 Gender disparities by subtopic

For each topic, we estimated the authorship proportion by gender and found that the proportion of men First Authors is higher than that of women First Authors across 10 of the 13 topics, except “Aging and Development,” “Pain,” and “Schizophrenia” (Figure 6a). For Last Authors, the proportion of men authors is much higher across all topics (Figure 6b). Along with differences in authorship, we also found that men authors had higher self-citation rates across all topics for both First and Last Authors (Figure 6c-d).

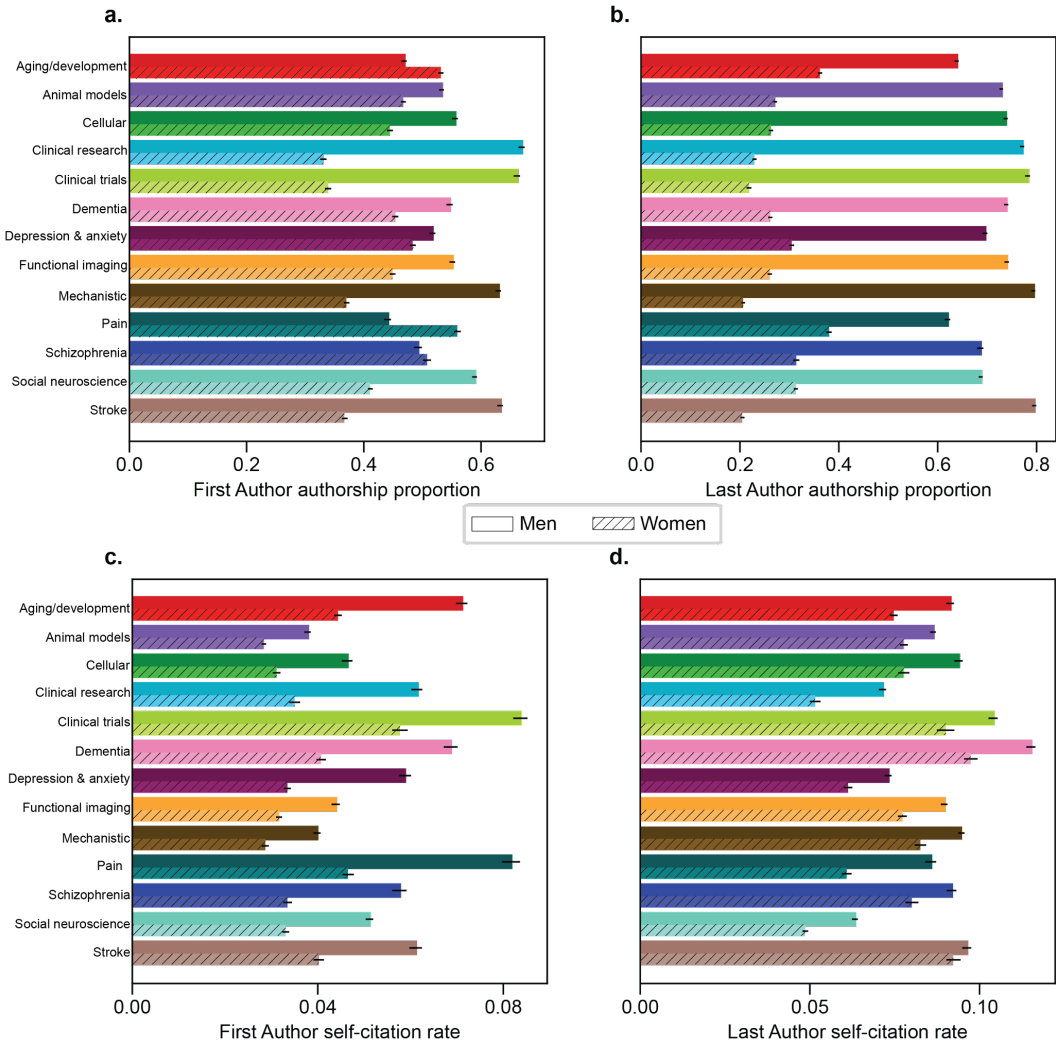

Figure 6. Gender disparities in authorship and self-citation by topic, using the same topics presented in Figure 5. **a)** Authorship by topic for First Authors. **b)** Authorship by topic for Last Authors. **c)** First Author self-citation rates by topic. **d)** Last Author self-citation rates by topic. Error bars represent 95% confidence intervals obtained from 1000 iterations of bootstrap resampling.

2.10 Self-citation rate for a particular author

Along with evaluating self-citation rates by topic, we also investigated self-citation rates for a particular author, in this case Dustin Scheinost. Dr. Scheinost permitted us to use his name and self-citation data in this work. We show a histogram of self-citations by paper (Figure 7a), the self-citation rates over time (Figure 7b), and the histogram of Any Author self-citation rates for all of Dr. Scheinost's papers (Figure 7c).

Self-citation rates for particular authors may be of interest for authors to evaluate and regulate their self-citations and to better understand individual trajectories in self-citation rates. Furthermore, these methods can be extended to evaluate self-citation rates at the level of a country, institute, or journal. For instance, we compared self-citation rates in Nature Neuroscience to the overall field of neuroscience (Figure S8).

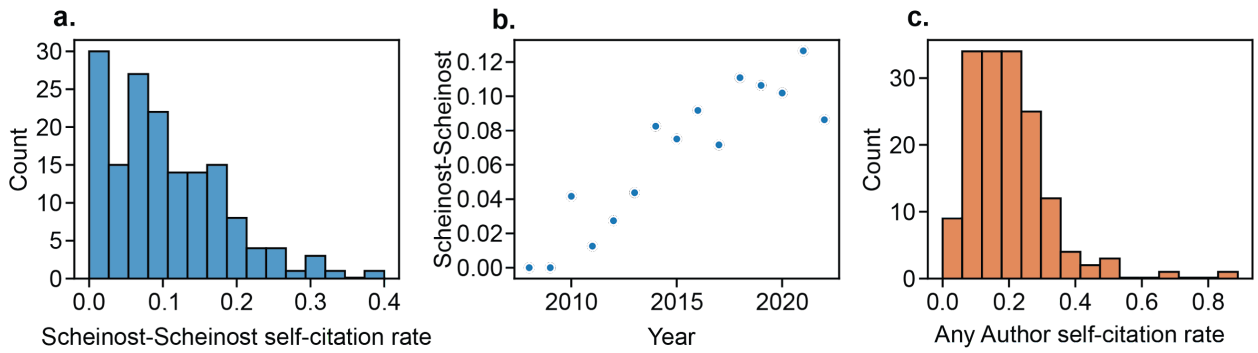

Figure 7. Single author self-citation rates for Dustin Scheinost. **a)** Histogram of Scheinost-Scheinost self-citation rates, which were computed as the proportion of references with Scheinost as an author across every paper. **b)** Scheinost-Scheinost self-citation rate over time. **c)** Any Author self-citation rates for all papers with Scheinost as an author.

3. Discussion

This work analyzed self-citation rates in 157,001 peer-reviewed neurology, neuroscience, and psychiatry papers, with over eight million total citations. We calculated self-citation trends by academic age, across different countries, by gender, and across different subfields, which yielded several key findings. First, self-citation rates over the past two decades decreased for First Authors (by 2% since 2000), remained constant for Last Authors, and increased for Any Authors (by 1% since 2000). Second, self-citation rate was strongly correlated with academic age. Third, we characterized differences in self-citation by country and displayed them on a global map. Fourth, we found that men cited themselves more than women, as demonstrated by 41% higher self-citation rates in the early career stage, and men also had more papers than women of the same academic age. Fifth, although different topics had different self-citation rates, gender disparities remained pervasive across them. Notably, even though some of the differences in self-citation rates may seem small (<5%), a single self-citation increases the number of citations by other researchers by approximately one after a year and by three after five years, according to previous work modeling self-citations [17].

3.1 Temporal trends in self-citation rates

Increasing collaborations and expanding author lists through the years may explain the increase in Any Author self-citation rates. However, the decrease in First Author self-citation rates is potentially concerning, especially given the constant nature of Last Author self-citation rates. If senior authors maintain steady self-citation rates but junior authors are self-citing at a lower rate, this could exacerbate citation discrepancies by seniority level. These discrepancies could make it harder for junior authors to advance their careers, warranting further investigation and monitoring.

The finding of increasing academic age relating to increased self-citation rates is not surprising because, as one continues in their career, they contribute to more papers and thus are more likely to cite themselves. However, these results demonstrate a “snowball effect,” whereby senior authors continually accumulate a disproportionate number of self-citations. For example, an author with 50 years of experience cites themselves approximately twice as much as one with 15 years of experience on average. Both authors have plenty of works that they can cite, and likely only a few are necessary. As such, we encourage authors to be cognizant of their citations and to only cite themselves when necessary, such as when a new work directly builds upon their previous work.

3.2 Geographic differences in self-citation rates

In cases where academic hiring depends heavily on citation metrics, such as a controversial policy in Italy where citations influence promotions, people will be motivated to “game the system,” including through self-citation [25]. Each country and individual institution may value quantitative publication metrics differently in the hiring and promotion process, which could be a potential cause of the differences in self-citation rate by country. Ideally, authors, journals, and countries would work together to establish self-citation guidelines and discourage a “game the system” mindset.

3.3 Gender disparities in self-citation rates

Since citation metrics may play a role in hiring and career decisions, citations must not be biased toward a particular group. The higher self-citation rate of men compared to women aligns with previous self-citation literature [7,16] and publications suggesting that men tend to promote their work more highly than women [26]. Crucially, the self-citation disparity emerged early in their careers, when citations may be the most significant in determining career trajectory, progress, and success. Part of this discrepancy was from men citing themselves more than women who have authored a similar number of papers, which could be due to differences in potential mentorship of men and women or broader societal differences. Another contributing factor to the self-citation difference was that men generally co-authored more papers than women, even early in their careers. This naturally leads to fewer self-citations for women, and it may reflect that women are less extensively included in co-authorship networks than men [27,28]. These

self-citation and authorship discrepancies could contribute to the “leaky pipeline” of women in STEM [29], which contributes to disparities in academic faculty positions [30–32], editorial boards [33], and awards [34]. Nevertheless, future work is needed to determine if and how lower self-citation rates contribute to these outcomes.

3.4 Subfield differences in self-citation rates

The 13 subtopics under examination had different self-citation rates, and “acceptable levels" of self-citation may vary depending on the subfield. For example, clinical trials had the highest self-citation rate, which may relate to the relatively high number of authors per paper in clinical trial research or the fact that clinical trial research often builds upon previous interventions (e.g., Phase 1 or 2 trials). Regardless of differences between topics, men self-cited at a higher rate than women within every single topic, even in subfields within which women First Authors were more common than men (e.g., Aging & development, Pain, Schizophrenia research). This suggests that self-citation gender disparities may not be due to inequality in a specific field but rather to widespread, structural inequalities in academia.

3.5 Limitations

There were several notable limitations of this study. First, as described above, we evaluated gender differences with gender assignment based on name, and this does not account for nonbinary, transgender, or intersex authors. Second, our analyses were restricted to the top-ranked neuroscience, neurology, and psychiatry journals, and the generalizability of these findings to a wider variety of journals has yet to be determined. However, limiting our analyses to this subset of journals facilitated more nuanced analyses of First, Any, and Last Author self-citation rates, which would not have been feasible across all journals in these disciplines. Third, we calculated differences between neuroscience, neurology, and psychiatry journals by assigning each journal to only one field (Table S1). As some journals publish across multiple fields (e.g., both neuroscience and psychiatry research), this categorization provides a gross estimate of differences between fields. Fourth, we reported averages of self-citation rates across various groups (e.g., academic ages), but there is a wide inter-author and inter-paper variability in self-citation rate. Fifth, selecting subtopics using LDA was subjective because we assigned each subtopic name based on the most common words. Despite these limitations, we found significant differences in self-citation rates for various groups, and thus we encourage authors and journals to explore their trends in self-citation rates.

3.6 Conclusions

Overall, authors, editors, funding agencies, and departments should be aware of the potential effects of self-citation and strive to limit self-citations as much as is reasonable. The first step to working toward fair self-citation practices is for authors and journals to be aware of their self-citation rates and focus on changing them when necessary. The definition of self-citation used here harmonizes with that goal because it is calculable on the level of a single article and thus can be applied to evaluate self-citation rates of individual articles, specific authors, journals,

institutions, or countries. We hope that this work and our code, which enables authors to evaluate their self-citation rates (https://github.com/mattrosenblatt7/self_citation), will contribute to a more fair future of citation practices in neuroscience research.

4. Methods

We collected data from the 25 journals with the highest impact factors, based on Web of Science impact factors, in each of neurology, neuroscience, and psychiatry. Some journals appeared in the top 25 list of multiple fields (e.g., both neurology and neuroscience), so 63 journals were ultimately included in our analysis.

4.1 Dataset collection

The data were downloaded from Scopus API in 2021-2022 via http://api.elsevier.com and http://www.scopus.com. We obtained information about research and review articles in the 63 journals from 2000-2020. We downloaded two sets of .csv files: 1) an article database and 2) a reference database. For each year/journal, the article database contains last names and first initials of the authors, title, year, and article EID (a unique identifier assigned by Scopus) of all research and review articles. The reference database contains the same information for all articles referenced by any article in the article database.

4.2 Python code using Pybliometrics API

We used the Pybliometrics API [18] to access citation information for each entry in the article database. First, we used the article EID to retrieve a detailed author list, which included full names and Scopus Author IDs, and a list of references for each article. The list of references included author names with the format “Last Name, First Initial.” To reduce the number of calls to the API, we only retrieved more information about references that included the author of interest by last name and first initial. For all these references with matching “Last Name, First Initial,” we retrieved more detailed information, including full author names and Scopus Author IDs.

To count as a self-citation, we required that the Scopus Author IDs matched exactly or that the first and last names matched exactly. While we recognize that some authors may have the exact same first and last names, the vast majority of self-citations with matching names will be correctly counted. If both Scopus Author IDs and full names were not available on Scopus, then we matched only based on last name and first initial.

Our self-citation metrics included First Author, Last Author, and Any Author self-citation rates. For First (Last) Author self-citation rates, we computed the proportion of reference papers on which the citing First (Last) author is also an author. We considered papers with only a single author as both First Author and Last Author self-citations. For Any Author self-citation rates, we found the proportion of papers for which at least one of the citing authors (any authorship position) was also an author. For the analyses in this paper, we reported total (or weighted

average) self-citation rates for different groups. For example, in Figure 1, the reported self-citation rate for the year 2000 is the total number of self-citations in 2000 across all papers divided by the total number of references in 2000 across all papers.

Other data we collected from Scopus and Pybliometrics included the affiliation of the authors, the number of papers published by the First and Last Authors before the current paper, and academic age of the First and Last Authors, which we defined as the time between the author's first publication and their current publication.

4.3 Country affiliation

For both First and Last Authors, we found the country of their current institutional affiliation. We then calculated the total First Author and Last Author self-citation rate by country, only including countries that had at least 50 First Author or Last Author papers in these select journals from 2016-2020. We then projected the self-citation rates onto a map using Geopandas [20], specifically using the map with coordinate systems EPSG:6933 (https://epsg.io/6933).

4.4 Name gender probability estimation

To compute gender probabilities, we submitted given names of all First and Last Authors to the Genderize.io Python API. Each name was assigned a probability of a name belonging to a woman or man, and we only used names for which Genderize.io assigned at least an 80% probability. Details about the Genderize.io database used to calculate probabilities is available at this link: https://genderize.io/our-data.

There are clear limitations to probabilistically assigning genders to names with packages such as Genderize.io, as described in [7], because they assume genders are binary and do not account for authors who identify as nonbinary, transgender, or intersex. As such, the terms "women" and "men" indicate the probability of a name being that gender and not that a specific author identifies as a man or woman. However, these tools are still useful to explore broad trends in self-citation rates for women and men.

4.5 Topic modeling

Latent Dirichlet Allocation (LDA) [35,36] was implemented with the Gensim package [37] in Python. LDA is a generative probabilistic model that is commonly used in natural language processing to discover topics in a large set of documents. In LDA, each document is modeled as a distribution of latent topics, and each topic is represented as a distribution of words. Based on the data provided, in this case abstracts from all articles in our dataset from 2016-2020, the model finds distributions of topics and words to maximize the log likelihood of the documents. Further details about LDA are available in [35–37].

For our implementation, we first removed all special characters and numbers from the abstract data. Then, we lemmatized the words using the Natural Language Toolkit [38]. We excluded words

that appeared in less than 20 documents, words that appeared in over 50% of the documents, common stop words (e.g., “the”, “you”, etc.), and some additional words that we felt would not meaningfully contribute to the topic model (e.g., “associated”, “analysis”, “effect”, etc.). In addition, we allowed for bigrams (two consecutive words) and trigrams (three consecutive words) in the model, as long as they appeared at least 20 times in the dataset.

Our total corpus included 41,434 documents with 16,895 unique tokens (words + bigrams + trigrams). We used 90% of the corpus to train our LDA model, and left out 10% to evaluate the perplexity, where a lower perplexity demonstrates better performance, as described in [35]. For the a-priori belief on document-topic distribution, we used Gensim’s “auto” option. We trained models with a number of topics ranging from 2-20, passing through the entire train corpus 30 times for each number of topics we evaluated. The number of topics was picked based on two evaluation metrics. First, we selected 13 topics as the topics that seemed most meaningful, as assessed qualitatively by word clouds for each topic. Second, we selected seven topics as the number of topics with the lowest validation perplexity.

Finally, we assigned each paper a discrete topic by choosing the topic with highest probability. Since we do not necessarily care about the generalization of this model and are instead using it to determine topics of a specific set of papers, we determined topics on the same data on which the model was trained.

4.6 Self-citation rate for a particular author

We also calculated the self-citation rate for a particular author, in this case Dustin Scheinost, in Figure 7. Here, we defined Scheinost-Scheinost self-citation rates as the proportion of references with Dr. Scheinost as one of the authors. Notably, Dr. Scheinost can be in any author position on the citing or cited article. In Figure 7c, we calculated the Any Author self-citation rate for all of Dr. Scheinost’s papers.

4.7 Confidence Intervals

Confidence intervals were computed with 1000 iterations of bootstrap resampling at the article level. For example, of the 157,001 articles in the dataset, we resampled articles with replacement and recomputed all results. The 95% confidence interval was reported as the 2.5 and 97.5 percentiles of the bootstrapped values.

4.8 P values

P values were computed with permutation testing using 10,000 permutations, with the exception of regression P values. For comparing different fields (e.g., neuroscience and psychiatry) and comparing self-citation rates of men and women, the labels were randomly permuted to obtain null distributions. For comparing self-citation rates between First and Last Authors, the first and last authorship was swapped with 50% probability for each paper.

In total, we made 40 comparisons. All P values described in the main text were corrected with the Bonferroni correction. With 10,000 permutations and 40 tests, the lowest P value after correction is $P<0.004$, which indicates that the true point would be the most extreme in the simulated null distribution. Further details about each comparison and P values can be found in Table S4.

4.9 Code and Data Availability

We have made code available to calculate your own self-citation rate at this link: https://github.com/mattrosenblatt7/self_citation. If you do not have access to Scopus or have difficulty running the code but are still interested in knowing your self-citation rate, please contact the authors.

4.10 Citation Diversity Statement

Recent work in several fields of science has identified a bias in citation practices such that papers from women and other minority scholars are under-cited relative to the number of such papers in the field [6–9,39–43]. Here we sought to proactively consider choosing references that reflect the diversity of the field in thought, form of contribution, gender, race, ethnicity, and other factors. First, we obtained the predicted gender of the First and Last Author of each reference by using databases that store the probability of a first name being carried by a woman [7,44]. By this measure (and excluding self-citations to the First and Last Authors of our current paper), our references contain 14.89% woman(first)/woman(last), 14.89% man/woman, 17.6% woman/man, and 52.61% man/man. This method is limited in that a) names, pronouns, and social media profiles used to construct the databases may not, in every case, be indicative of gender identity and b) it cannot account for intersex, non-binary, or transgender people. Second, we obtained predicted racial/ethnic category of the First and Last Author of each reference by databases that store the probability of a first and last name being carried by an author of color [45,46]. By this measure (and excluding self-citations), our references contain 8.45% author of color (first)/author of color(last), 16.24% white author/author of color, 15.98% author of color/white author, and 59.34% white author/white author. This method is limited in that a) names, Census entries, and Wikipedia profiles used to make the predictions may not be indicative of racial/ethnic identity, and b) it cannot account for Indigenous and mixed-race authors, or those who may face differential biases due to the ambiguous racialization or ethnicization of their names. We look forward to future work that could help us to better understand how to support equitable practices in science.

References

1. Greenberg, S. A. How citation distortions create unfounded authority: analysis of a citation network. *BMJ* **339**, b2680 (2009).
2. Van Noorden, R. Brazilian citation scheme outed. *Nature* **500**, 510–511 (2013).
3. Abbott, A. *et al.* Do metrics matter? Many researchers believe that quantitative metrics determine who gets hired and who gets promoted at their institutions. *Nature* (2010).
4. Else, H. Row erupts over university's use of research metrics in job-cut decisions. *Nature* **592**, 19 (2021).
5. Nielsen, M. W. & Andersen, J. P. Global citation inequality is on the rise. *Proc. Natl. Acad. Sci. U. S. A.* **118**, (2021).
6. Bertolero, M. A. *et al.* Racial and ethnic imbalance in neuroscience reference lists and intersections with gender. *bioRxiv* 2020.10.12.336230 (2020) doi:10.1101/2020.10.12.336230.
7. Dworkin, J. D. *et al.* The extent and drivers of gender imbalance in neuroscience reference lists. *Nat. Neurosci.* **23**, 918–926 (2020).
8. Chatterjee, P. & Werner, R. M. Gender Disparity in Citations in High-Impact Journal Articles. *JAMA Network Open* vol. 4 e2114509 (2021).
9. Fulvio, J. M., Akinnola, I. & Postle, B. R. Gender (Im)balance in Citation Practices in Cognitive Neuroscience. *Journal of Cognitive Neuroscience* vol. 33 3–7 (2021).
10. Holden, G., Rosenberg, G. & Barker, K. Bibliometrics: a potential decision making aid in hiring, reappointment, tenure and promotion decisions. *Soc. Work Health Care* **41**, 67–92 (2005).
11. Petersen, A. M. *et al.* Reputation and impact in academic careers. *Proc. Natl. Acad. Sci. U. S. A.* **111**, 15316–15321 (2014).
12. Ioannidis, J. P. A., Baas, J., Klavans, R. & Boyack, K. W. A standardized citation metrics

author database annotated for scientific field. *PLoS Biol.* **17**, e3000384 (2019).

13. Aksnes, D. W. A macro study of self-citation. *Scientometrics* **56**, 235–246 (2003).
14. Snyder, H. & Bonzi, S. Patterns of self-citation across disciplines (1980-1989). *J. Inf. Sci. Eng.* **24**, 431–435 (1998).
15. Bartneck, C. & Kokkelmans, S. Detecting h-index manipulation through self-citation analysis. *Scientometrics* **87**, 85–98 (2011).
16. King, M. M., Bergstrom, C. T., Correll, S. J., Jacquet, J. & West, J. D. Men Set Their Own Cites High: Gender and Self-citation across Fields and over Time. *Socius* **3**, 2378023117738903 (2017).
17. Fowler, J. H. & Aksnes, D. W. Does self-citation pay? *Scientometrics* **72**, 427–437 (2007).
18. Rose, M. E. & Kitchin, J. R. pybliometrics: Scriptable bibliometrics using a Python interface to Scopus. *SoftwareX* **10**, 100263 (2019).
19. Bardeesi, A. M., Jamjoom, A. A. B., Sharab, M. A. & Jamjoom, A. B. Impact of country self citation on the ranking of the top 50 countries in clinical neurology. *eNeurologicalSci* **23**, 100333 (2021).
20. Jordahl, K. *et al. geopandas/geopandas: v0.8.1*. (2020). doi:10.5281/zenodo.3946761.
21. Ginther, D. K. & Hayes, K. J. Gender Differences in Salary and Promotion in the Humanities. *Am. Econ. Rev.* **89**, 397–402 (1999).
22. Deutsch, F. M. & Yao, B. Gender differences in faculty attrition in the USA. *Community Work Fam.* **17**, 392–408 (2014).
23. Li, B. *et al.* Gender differences in faculty rank among academic physicians: a systematic review and meta-analysis. *BMJ Open* **11**, e050322 (2021).
24. Casad, B. J. *et al.* Gender inequality in academia: Problems and solutions for women faculty in STEM. *J. Neurosci. Res.* **99**, 13–23 (2021).
25. Seeber, M., Cattaneo, M., Meoli, M. & Malighetti, P. Self-citations as strategic response to the use of metrics for career decisions. *Res. Policy* **48**, 478–491 (2019).

26. Lerchenmueller, M. J., Sorenson, O. & Jena, A. B. Gender differences in how scientists present the importance of their research: observational study. *BMJ* **367**, l6573 (2019).
27. Zeng, X. H. T. *et al.* Differences in Collaboration Patterns across Discipline, Career Stage, and Gender. *PLoS Biol.* **14**, e1002573 (2016).
28. Li, W., Zhang, S., Zheng, Z., Cranmer, S. J. & Clauset, A. Untangling the network effects of productivity and prominence among scientists. *Nat. Commun.* **13**, 4907 (2022).
29. Pell, A. N. Fixing the leaky pipeline: women scientists in academia. *J. Anim. Sci.* **74**, 2843–2848 (1996).
30. Smith, D. O. Gender disparity in the academic pipeline: women in neuroscience. *Synapse* **14**, 332–334 (1993).
31. Nguyen, A. X. *et al.* Gender Gap in Neurology Research Authorship (1946–2020). *Front. Neurol.* **12**, (2021).
32. Wapman, K. H., Zhang, S., Clauset, A. & Larremore, D. B. Quantifying hierarchy and dynamics in US faculty hiring and retention. *Nature* 1–8 (2022).
33. Palser, E. R., Lazerwitz, M. & Fotopoulou, A. Gender and geographical disparity in editorial boards of journals in psychology and neuroscience. *Nat. Neurosci.* **25**, 272–279 (2022).
34. Melnikoff, D. E. & Valian, V. V. Gender Disparities in Awards to Neuroscience Researchers. *Arch Sci Psychol* **7**, 4–11 (2019).
35. Blei, D. M., Ng, A. Y. & Jordan, M. I. Latent dirichlet allocation. *J. Mach. Learn. Res.* (2003).
36. Hoffman, M., Bach, F. & Blei, D. M. Online learning for latent dirichlet allocation. *Adv. Neural Inf. Process. Syst.* (2010).
37. Rehurek, R. & Sojka, P. Software Framework for Topic Modelling with Large Corpora. in *Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks* (2010).
38. Bird, S., Klein, E. & Loper, E. *Natural Language Processing with Python: Analyzing Text with the Natural Language Toolkit*. ('O'Reilly Media, Inc.', 2009).
39. Mitchell, S. M., Lange, S. & Brus, H. Gendered citation patterns in international relations

journals. *International Studies Perspectives* **14**, 485–492 (2013).

40. Maliniak, D., Powers, R. & Walter, B. F. The Gender Citation Gap in International Relations. *International Organization* vol. 67 889–922 (2013).
41. Caplar, N., Tacchella, S. & Birrer, S. Quantitative evaluation of gender bias in astronomical publications from citation counts. *Nature Astronomy* **1**, 1–5 (2017).
42. Dion, M. L., Sumner, J. L. & Mitchell, S. M. Gendered Citation Patterns across Political Science and Social Science Methodology Fields. *Political Analysis* vol. 26 312–327 (2018).
43. Wang, X. *et al.* Gendered Citation Practices in the Field of Communication. *Ann Int Commun Assoc* **45**, 134–153 (2021).
44. Zhou, D., Cornblath, E. J., Stiso, J., Teich, E. G. & Dworkin, J. D. Gender diversity statement and code notebook v1. 0. *Zenodo* (2020).
45. Ambekar, A., Ward, C., Mohammed, J., Male, S. & Skiena, S. Name-ethnicity classification from open sources. in *Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining* 49–58 (Association for Computing Machinery, 2009).
46. Sood, G. & Laohaprapanon, S. Predicting Race and Ethnicity From the Sequence of Characters in a Name. *arXiv [stat.AP]* (2018).

Supplement

S1. All journals included in these analyses

Table S1 shows all 63 journals included in our dataset. We categorized each journal as belonging to neurology, neuroscience, or psychiatry. While we recognize that some journals belong to overlapping fields (e.g., neurology and neuroscience), we attempted to select the most relevant field for each journal.

Field	**Journals**
Neurology	Acta Neuropathologica; Alzheimer's and Dementia; Alzheimer's Research and Therapy; Annals of Neurology; Brain; Brain Stimulation; Epilepsy Currents; JAMA Neurology; JNNP; Journal of Headache and Pain; Journal of Stroke; Lancet Neurology; Molecular Neurodegeneration; Movement Disorders; Nature Reviews Neurology; Neuro-Oncology; Neurology; Neurology: Neuroimmunology and NeuroInflammation; Neuropathology and Applied Neurobiology; Neurotherapeutics; npj Parkinson's Disease; Pain; Sleep Medicine Reviews; Stroke; Translational Stroke Research
Neuroscience	Annual Review of Neuroscience; Behavioral and Brain Sciences; Brain, Behavior, and Immunity; Frontiers in Neuroendocrinology; Journal of Neuroinflammation; Journal of Pineal Research; Nature Human Behaviour; Nature Neuroscience; Nature Reviews Neuroscience; Neuron; Neuroscience and Biobehavioral Reviews; Neuroscientist; Progress in Neurobiology; Trends in Cognitive Sciences; Trends in Neurosciences
Psychiatry	Acta Psychiatrica Scandinavica; Addiction; American Journal of Psychiatry; Biological Psychiatry; Bipolar Disorders; Body Image; British Journal of Psychiatry; Clinical Psychological Science; Depression and Anxiety; Epidemiology and Psychiatric Sciences; Evidence-Based Mental Health; JAACAP; JAMA Psychiatry; JCPP; Journal of Abnormal Psychology; Journal of Behavioral Addictions; Molecular Psychiatry; Neuropsychopharmacology; Psychological Medicine; Psychotherapy and Psychosomatics; Schizophrenia Bulletin; The Lancet Psychiatry; World Psychiatry

Table S1. All journals included in this analysis by field, sorted alphabetically.

S2. Comparison of estimated and manual scoring of self-citation

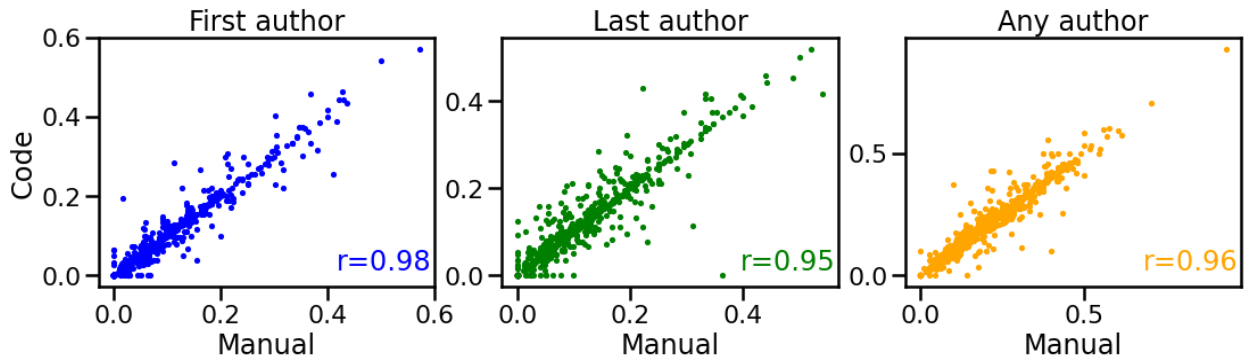

Figure S1. Comparison between manual scoring of self-citation rates and self-citation rates estimated from Python scripts in 5 psychiatry journals: American Journal of Psychiatry, Biological Psychiatry, JAMA Psychiatry, Lancet Psychiatry, and Molecular Psychiatry. 906 articles in total were manually evaluated (10 articles per journal per year from 2000-2020, four articles excluded for very large author list lengths and thus high difficulty of manual scoring).

S3. Temporal trends in self-citation rate by field

We repeated the analysis in Figure 1b after separating the papers into neurology, neuroscience, and psychiatry. In addition, correlations and slopes between year and self-citation rate are reported in Table S2. Notably, Last Author and Any Author self-citation rates are increasing in neurology and psychiatry but decreasing in neuroscience.

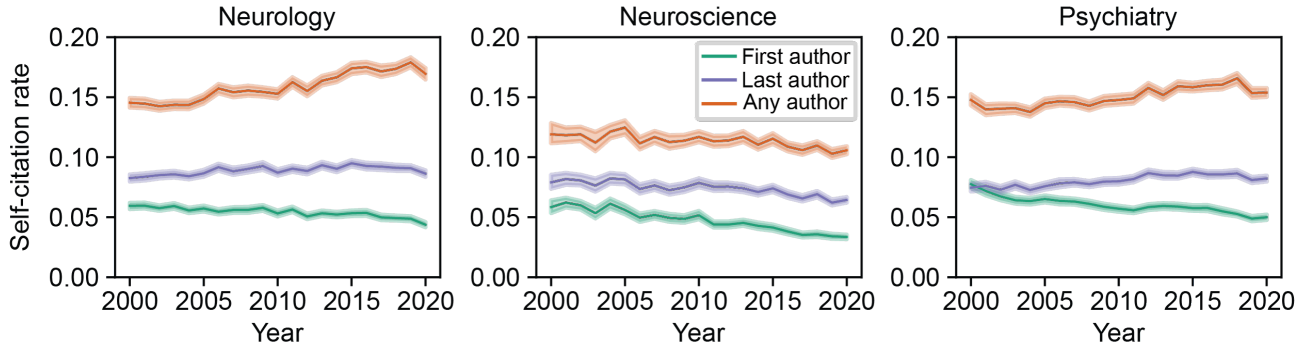

Figure S2. Temporal trends in First Author, Last Author, and Any Author self-citation rates from 2000-2020 in neurology, neuroscience, and psychiatry papers. Shaded regions show 95% confidence intervals calculated with bootstrap resampling.

		Correlation	Slope (% per decade)
Neurology	**First Author**	-0.854 (-0.912, -0.788)	-0.582 (-0.672, -0.497)
	Last Author	0.625 (0.488, 0.745)	0.380 (0.284, 0.472)
	Any Author	0.927 (0.898, 0.953)	1.798 (1.641, 1.949)
Neuroscience	**First Author**	-0.952 (-0.975, -0.922)	-1.422 (-1.544, -1.303)
	Last Author	-0.826 (-0.898, -0.735)	-0.801 (-0.937, -0.665)
	Any Author	-0.687 (-0.821, -0.528)	-0.665 (-0.861, -0.477)
Psychiatry	**First Author**	-0.902 (-0.935, -0.864)	-1.007 (-1.098, -0.912)
	Last Author	0.803 (0.726, 0.868)	0.638 (0.539, 0.744)
	Any Author	0.813 (0.743, 0.874)	1.070 (0.929, 1.223)

Table S2. Correlations between year and self-citation rate and corresponding slopes by field.

S4. Self-citation rates by country

Country	First Author Self-citation Rate	Last Author Self-citation Rate
Argentina	3.04 (2.22, 3.93)	**Not enough papers**
Australia	4.65 (4.35, 4.92)	6.97 (6.66, 7.30)
Austria	4.78 (3.74, 5.80)	7.54 (6.59, 8.55)
Belgium	4.25 (3.68, 4.75)	7.14 (6.42, 7.81)
Brazil	2.97 (2.42, 3.47)	7.39 (6.60, 8.24)
Canada	4.13 (3.86, 4.38)	7.51 (7.22, 7.83)
China	2.41 (2.27, 2.56)	5.35 (5.12, 5.60)
Czech Republic	3.30 (2.25, 4.72)	4.84 (3.28, 6.85)
Denmark	4.25 (3.82, 4.66)	7.62 (7.03, 8.22)
Finland	5.21 (4.39, 6.02)	8.73 (7.78, 9.70)
France	3.99 (3.72, 4.26)	7.47 (7.11, 7.86)
Germany	4.83 (4.61, 5.05)	8.65 (8.38, 8.94)

Greece	5.36 (4.13, 6.83)	5.56 (4.22, 7.23)
Hungary	4.99 (3.93, 6.13)	7.53 (6.23, 9.09)
India	2.74 (2.16, 3.35)	4.73 (3.79, 5.84)
Iran	1.44 (0.82, 2.13)	2.53 (1.65, 3.51)
Israel	3.68 (3.04, 4.28)	6.86 (6.21, 7.50)
Italy	5.54 (5.22, 5.86)	7.68 (7.30, 8.07)
Japan	4.79 (4.38, 5.22)	8.78 (8.30, 9.32)
Mexico	**Not enough papers**	6.24 (4.55, 7.91)
Netherlands	3.98 (3.73, 4.24)	7.37 (7.05, 7.73)
New Zealand	5.18 (4.07, 6.39)	6.98 (6.02, 8.12)
Norway	4.61 (3.97, 5.24)	7.30 (6.60, 8.07)
Poland	3.15 (2.49, 3.86)	5.33 (4.03, 6.89)
Portugal	2.45 (1.96, 2.97)	4.56 (3.81, 5.30)
Russia	**Not enough papers**	7.87 (6.07, 9.90)
Singapore	3.58 (2.71, 4.48)	6.31 (5.48, 7.27)
South Africa	**Not enough papers**	5.82 (4.66, 7.11)
Spain	3.91 (3.60, 4.21)	7.18 (6.68, 7.74)
Sweden	5.16 (4.70, 5.63)	8.80 (8.34, 9.25)
Switzerland	4.60 (4.20, 4.98)	8.06 (7.56, 8.56)
Taiwan	3.59 (3.16, 4.02)	7.33 (6.59, 8.08)
Turkey	3.83 (2.62, 5.33)	5.49 (4.04, 7.20)
United Kingdom	5.11 (4.91, 5.29)	8.52 (8.28, 8.76)
United States	4.73 (4.64, 4.83)	8.50 (8.40, 8.62)

Table S3. First Author and Last Author self-citation rates by affiliation country of the author for papers from 2016-2020. 95% confidence intervals obtained via bootstrap resampling are included in parentheses. Only countries with at least 50 papers were included in the analysis.

S5. Comparison of self-citation rates by gender for a given number of papers

We categorized authors based on the number of previous papers they had at the time of publication. We then evaluated the self-citation rates by number of papers for women and men.

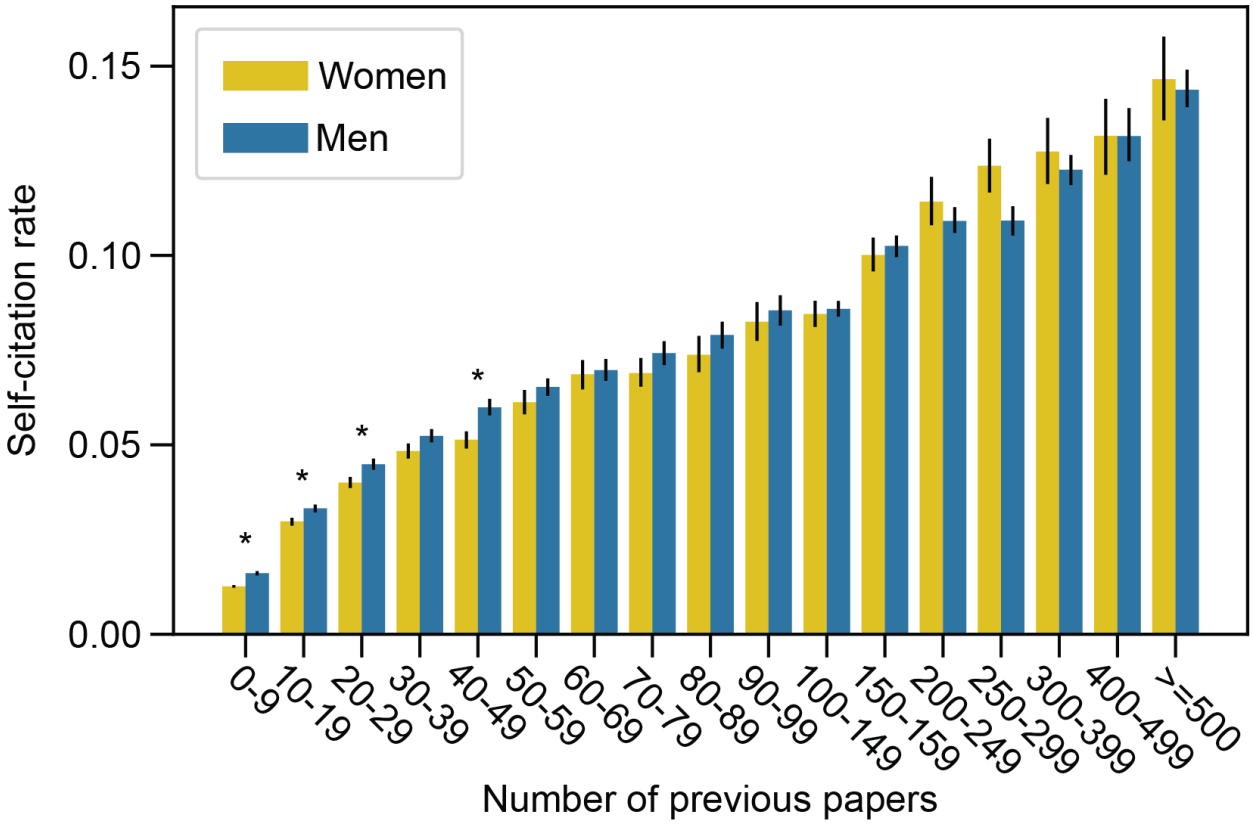

Figure S3. Self-citation rates by number of papers for women and men. Error bars reflect 95% confidence intervals obtained with bootstrap resampling. Significant differences (permutation test, corrected $P<0.05$) between women and men are signified by an asterisk.

S6. Latent dirichlet allocation

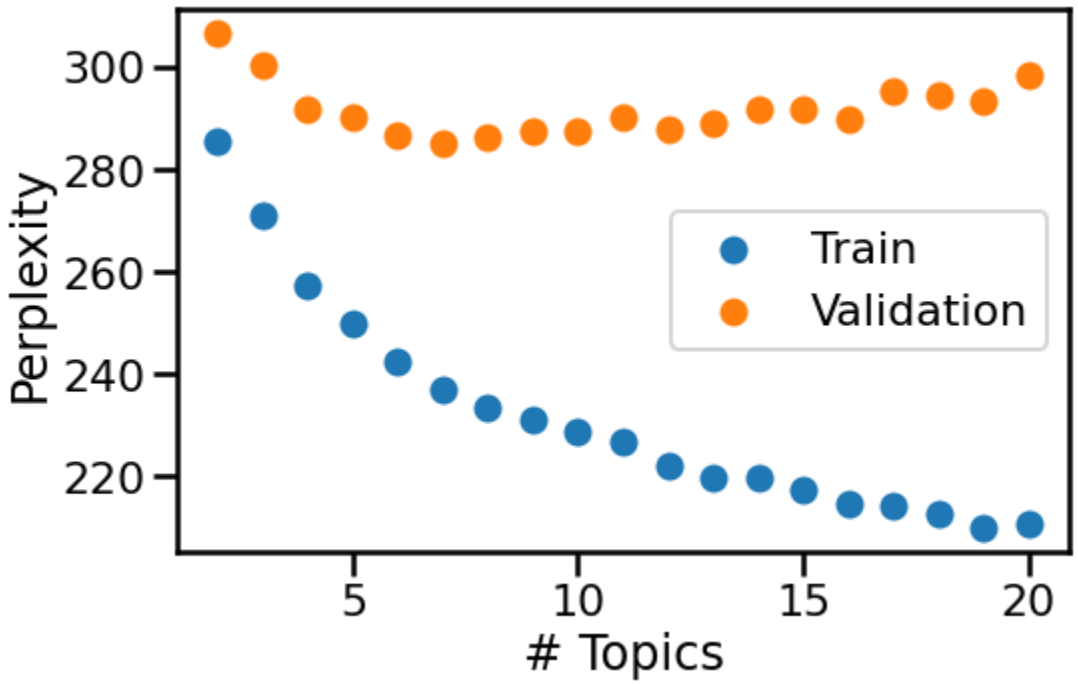

Figure S4. LDA perplexity on training and validation data for a different number of topics. The lowest validation perplexity was for seven topics.

Figure S5. Topic word clouds for 13 topics. These are the most common words appearing in each of our LDA model topics. Based on the word clouds, we assigned overall themes, or topic names.

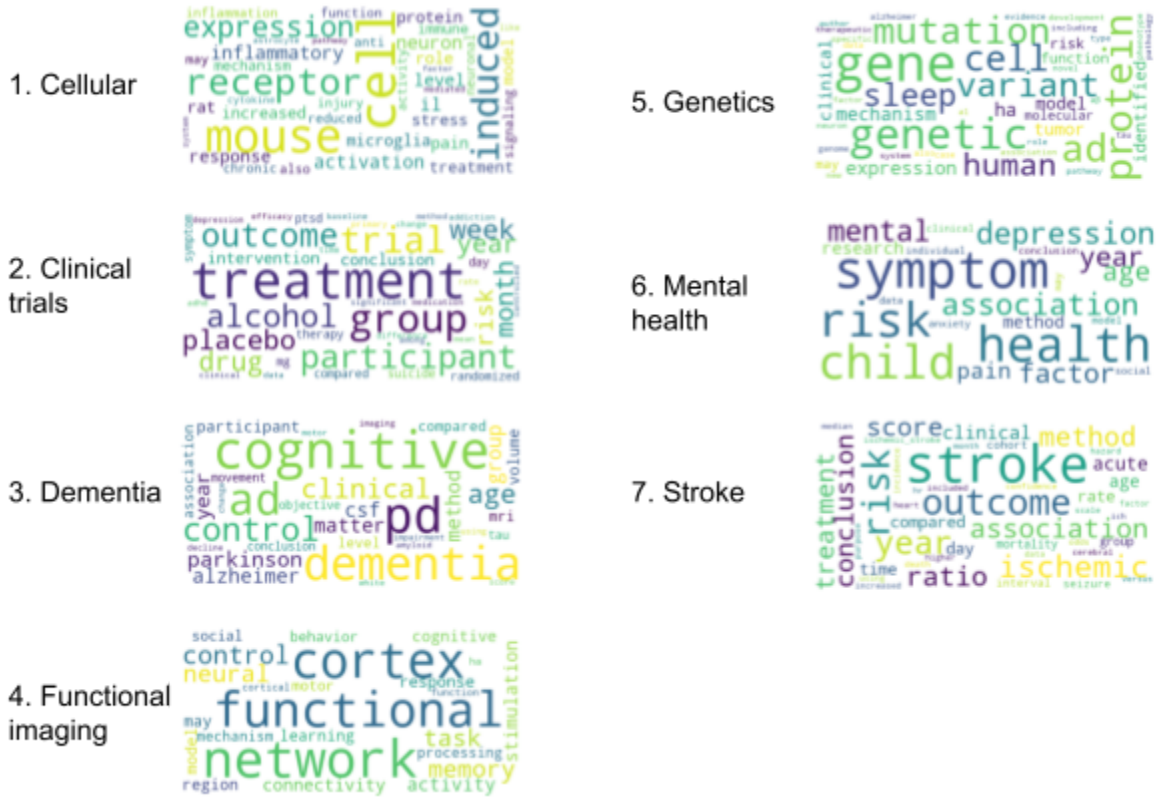

Figure S6. Topic word clouds for seven topics. These are the most common words appearing in each of our LDA model topics. Based on the word clouds, we assigned overall themes, or topic names.

The results for self-citation rates with seven topics show similar trends as the results for 13 topics. For example, both Clinical trials and Dementia have high self-citation rates whether using seven or 13 topics.

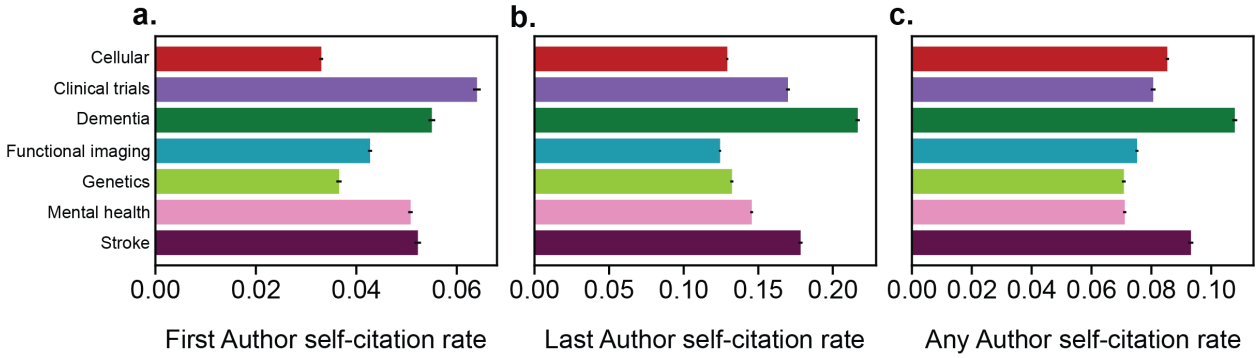

Figure S7. a) First Author, **b)** Last Author, and **c)** Any Author self-citation rates for seven topics.

S7. Self-citation rates in Nature Neuroscience

We compared self-citation rates in a single journal (Nature Neuroscience) to the entire field of neuroscience. In general, Last Author and Any Author self-citation rates were higher in Nature Neuroscience compared to the field. First Author self-citation rates used to be lower in Nature Neuroscience (e.g., Year 2000) but are now approximately equal to that of the field.

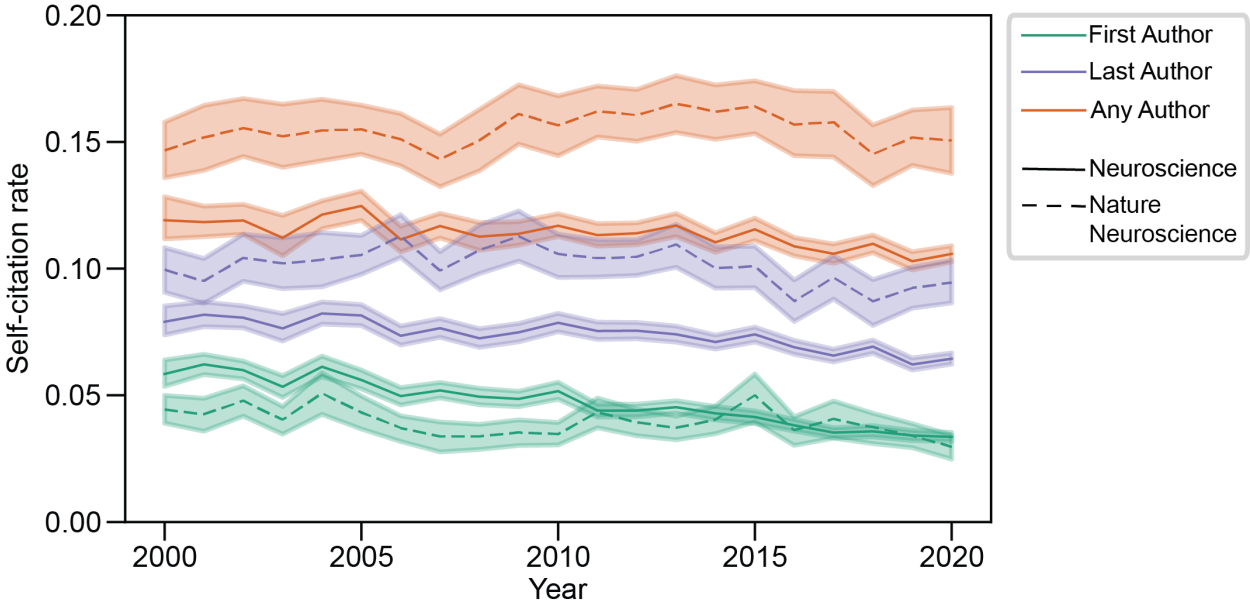

Figure S8. Comparison of self-citation rates in the entire field of neuroscience and the journal Nature Neuroscience.

S8. Summary of all comparisons

Comparison	**Finding**	**Method**	**Uncorrected *P***	**Corrected *P***
First vs Last Author self-citation (all fields)	* Last > First	permutation	<0.0001	<0.004
First vs Last Author self-citation (Neurology)	* Last > First	permutation	<0.0001	<0.004
First vs Last Author self-citation (Neuroscience)	* Last > First	permutation	<0.0001	<0.004
First vs Last Author self-citation (Psychiatry)	* Last > First	permutation	<0.0001	<0.004
First Author: Neurology vs. Neuroscience	* Neurology > Neuroscience	permutation	<0.0001	<0.004
First Author: Neuroscience vs. Psychiatry	* Psychiatry > Neuroscience	permutation	<0.0001	<0.004
First Author: Neurology vs.	* Psychiatry >	permutation	0.0001	0.004

Psychiatry		Neurology			
Last Author: Neurology vs. Neuroscience		* Neurology > Neuroscience	permutation	<0.0001	<0.004
Last Author: Neuroscience vs. Psychiatry		* Psychiatry > Neuroscience	permutation	<0.0001	<0.004
Last Author: Neurology vs. Psychiatry		* Neurology > Psychiatry	permutation	<0.0001	<0.004
Any Author: Neurology vs. Neuroscience		* Neurology > Neuroscience	permutation	<0.0001	<0.004
Any Author: Neuroscience vs. Psychiatry		* Psychiatry > Neuroscience	permutation	<0.0001	<0.004
Any Author: Neurology vs. Psychiatry		* Neurology > Psychiatry	permutation	<0.0001	<0.004
Slope over the years: First Author		* *m* = -1.05% / decade	correlation	2.64E-14	1.06E-12
Slope over the years: Last Author		*m* = -0.05% / decade	correlation	0.848	1
Slope over the years: Any Author		* *m* = 0.54% / decade	correlation	0.0001	0.0004
Men vs. Women, First Author self-citation rate, 2020		* Men > Women	permutation	<0.0001	<0.004
Men vs. Women, Last Author self-citation rate, 2020		* Men > Women	permutation	<0.0001	<0.004
Early career men vs. women, self-citation rate		* Men > Women	permutation	<0.0001	<0.004
Early career men vs. women, number of papers		* Men > Women	permutation	<0.0001	<0.004
Early career men vs. women self-citation rate by number of papers	0-9 papers	* Men > Women	permutation	<0.0001	<0.004
	10-19	* Men > Women	permutation	0.0003	0.012
	20-29	* Men > Women	permutation	0.0005	0.02
	30-39	Men > Women	permutation	0.0243	0.972
	40-49	* Men > Women	permutation	<0.0001	<0.004
	50-59	Men > Women	permutation	0.1223	1
	60-69	Men > Women	permutation	0.7009	1
	70-79	Men > Women	permutation	0.1191	1
	80-89	Men > Women	permutation	0.2263	1

	90-99	Men > Women	permutation	0.559	1
	100-149	Men > Women	permutation	0.6833	1
	150-199	Men > Women	permutation	0.3959	1
	200-249	Women > Men	permutation	0.2425	1
	250-299	Women > Men	permutation	0.0074	0.296
	300-399	Women > Men	permutation	0.504	1
	400-499	Women > Men	permutation	0.9194	1
	>=500	Women > Men	permutation	0.968	1
First Author: Spearman's correlation between topic self-citation and number of authors		r_{rank}=0.1484	correlation	0.6286	1
Last Author: Spearman's correlation between topic self-citation and number of authors		r_{rank}=0.6648	correlation	0.0132	0.52664
Any Author: Spearman's correlation between topic self-citation and number of authors		r_{rank}=0.7747	correlation	0.0019	0.07484

Table S4. *P* values for all 40 comparisons performed in this study. *P* values are corrected for multiple comparisons with the Bonferroni correction. For *P* values determined by permutation testing, 10,000 permutations were used. After correction, this means that a point more extreme than any in the null distribution would have $P<0.004$. Significant values ($P_{corrected}<0.05$) are marked with an asterisk in the "Finding" column.