Billions at Stake: How Self-Citation Adjusted Metrics Can Transform Equitable Research Funding

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***Abstract*—Citation metrics like the h-index and i10-index are widely used to evaluate scholarly impact, but they are vulnerable to inflation through self-citations. This paper introduces the Self-Citation Adjusted Index (SCAI), a novel metric that adjusts citation counts by accounting for self-citation patterns. Using data from 5,000 researcher profiles across diverse disciplines, we demonstrate that excessive self-citation can inflate traditional metrics by 10-20%, potentially misdirecting billions in research funding. Our open-source implementation provides tools for calculating SCAI and related metrics. Results indicate that SCAI offers a more equitable assessment of research impact, with particular benefits for addressing gender disparities in citation practices. This work contributes to the growing movement toward more transparent and fair research evaluation methods in academia.**

***Index Terms*—citation analysis, research metrics, self-citation, h-index, research evaluation, bibliometrics**

I. Introduction

The assessment of scholarly impact through citation metrics plays a critical role in academic evaluation, funding allocation, hiring decisions, and career advancement [1], [2]. Traditional metrics such as the h-index [1] and i10-index [3] have become standard tools for quantifying research impact. However, these metrics share a fundamental limitation: they treat all citations equally, regardless of source, including self-citations where authors cite their own previous work [4], [5].

While self-citation is a legitimate and often necessary aspect of research continuity [6], evidence suggests that excessive self-citation can artificially inflate citation counts and distort perceived scholarly impact [5], [7]. Studies indicate that each self-citation generates approximately three additional citations over a five-year period [5], creating a compounding effect that significantly skews traditional metrics.

This distortion creates several systemic problems:

- Misrepresentation of genuine research influence and impact
- Potential misallocation of research funding based on inflated metrics
- Exacerbation of existing gender and field disparities, as studies show men self-cite up to 70% more than women [8]

The academic community increasingly recognizes these limitations [4], [9], [10], yet widely adopted alternatives remain elusive. This paper addresses this gap by introducing the Self-Citation Adjusted Index (SCAI), a novel metric designed to provide a more accurate assessment of scholarly impact by accounting for self-citation patterns.

The remainder of this paper is organized as follows: Section II presents the motivation and background for developing citation metrics that adjust for self-citation. Section III details our contributions, including the SCAI algorithm and its implementation. Section IV presents results from applying SCAI to a diverse dataset of researcher profiles. Section V discusses the implications of these findings for research evaluation and funding allocation. Finally, Section VI concludes with a summary of contributions and directions for future work.

II. Motivation and Background

A. Limitations of Current Citation Metrics

Traditional citation metrics fail to distinguish between self-citations and external citations, treating both as equal indicators of research impact. The h-index [1], defined as the maximum value h where a researcher has published h papers with at least h citations each, counts self-citations on par with external citations. Similarly, the i10-index [3], which measures the number of publications with at least 10 citations, does not differentiate citation sources.

This equivalence creates vulnerabilities in the evaluation system:

1) Strategic Self-Citation: Researchers can strategically increase their self-citation rates to boost citation counts [5], [11]. While some self-citation reflects natural research progression, excessive self-citation can be a form of strategic behavior aimed at artificially inflating metrics [7].

2) Compounding Effects: The impact of self-citation extends beyond the immediate count. Fowler and Aksnes [5] demonstrated that each self-citation generates approximately three additional citations over five years, creating a compounding effect that significantly amplifies the initial inflation.

3) Journal Impact Factor Manipulation: Similar issues exist at the journal level, where high self-citation rates can inflate journal impact factors [**?**]. Journals with excessive self-citation rates have been temporarily suppressed from citation reports [12].

B. Financial and Equity Implications

The distortion of citation metrics has far-reaching consequences that extend beyond academic recognition:

1) Research Funding Allocation: Citation metrics often inform funding decisions [13]. If a 10-20% metric inflation results in even a 10% misallocation of funds, the cumulative financial impact across the research ecosystem can be substantial. In the United States alone, federal research funding exceeds $100 billion annually [14], meaning potential misallocation could reach billions of dollars.

2) Gender Disparities: Analyses reveal significant gender disparities in self-citation practices, with men self-citing up to 70% more than women [8], [15]. When unadjusted citation metrics are used for evaluation, these disparities compound existing inequities in academia [16], [17].

3) Field Variations: Self-citation rates vary substantially across disciplines [6], [7]. Fields with naturally higher self-citation rates may appear more impactful when evaluated using traditional metrics, potentially skewing cross-disciplinary comparisons and funding allocations [10].

C. Previous Approaches

Several approaches have been proposed to address the limitations of traditional citation metrics:

1) Variants of the h-index: Numerous modifications to the h-index have been proposed, including the g-index [18], which gives more weight to highly cited papers, and the m-quotient [1], which normalizes the h-index by career length. However, few directly address self-citation.

2) Self-citation exclusion: Some citation databases offer the option to exclude self-citations when calculating metrics [19]. However, this approach treats all self-citations as invalid, ignoring their legitimate role in research continuity [6].

3) Field normalization: Field-normalized citation metrics aim to account for discipline-specific citation patterns [10]. While valuable for cross-field comparisons, these approaches typically do not specifically address self-citation bias.

These previous approaches either fail to address self-citation directly or take an overly simplistic view that does not recognize the nuanced role of self-citation in scholarly communication. Our work builds on these foundations while explicitly focusing on developing a metric that appropriately adjusts for self-citation patterns.

III. Contributions

A. Conceptual Framework

This paper introduces the Self-Citation Adjusted Index (SCAI), a novel metric designed to provide a more accurate and equitable measure of scholarly impact. The SCAI builds on the foundation of traditional citation metrics while incorporating adjustments for self-citation patterns.

Our framework recognizes three key principles:

1) Not all self-citations are problematic; moderate self-citation is a natural part of research continuity
2) The impact of self-citation on perceived scholarly influence is non-linear and compounds over time
3) Adjustment factors should be transparent, adaptable to different disciplines, and based on empirical evidence

Based on these principles, we developed a comprehensive approach to citation analysis that includes:

- The SCAI as the primary metric for assessing citation impact with self-citation adjustment
- The Self-Citation Ratio (SCR) as a complementary diagnostic tool
- The s-index to specifically track self-citation patterns over time

B. SCAI Algorithm

The Self-Citation Adjusted Index is calculated using the following algorithm:

$$SCAI = h - \alpha \cdot (SCR - \beta)^{\gamma} \cdot h \tag{1}$$

Where:

- h is the traditional h-index
- SCR is the Self-Citation Ratio (total self-citations divided by total citations)
- α is a field-specific calibration parameter (default: 0.5)
- β is a threshold for acceptable self-citation (default: 0.1, or 10%)
- γ is an exponential parameter that controls the penalty's growth rate (default: 1.5)

The algorithm applies a non-linear penalty to the h-index based on the degree to which a researcher's self-citation ratio exceeds the acceptable threshold. This approach:

- Allows moderate self-citation without penalty
- Applies progressively larger adjustments as self-citation rates increase
- Maintains proportionality to the original h-index
- Can be calibrated for different disciplinary norms

C. Open-Source Implementation

We have developed and released an open-source Python package, *scholar-citations* [**?**], to implement the SCAI and related metrics. The package is available on PyPI [**?**] and the source code is hosted on GitHub [**?**].

The implementation provides the following features:

- Data collection from major citation databases (Google Scholar, Scopus, Web of Science)
- Identification and classification of self-citations
- Calculation of traditional metrics (h-index, i10-index) and their self-citation-adjusted counterparts
- Field-specific calibration options
- Visualization tools for citation analysis
- Export functionality for further analysis

Code Snippet 1 demonstrates the basic usage of the package:

```
scholar-citations --help
[--max-papers MAX_PAPERS]
[--max-citations MAX_CITATIONS]
[--output OUTPUT]
[--visible]
[--debug] url
```

This implementation represents a significant contribution to the field of bibliometrics by providing accessible, open-source tools for calculating and analyzing self-citation-adjusted metrics.

IV. Results

A. Dataset and Methodology

To evaluate the effectiveness of the SCAI, we analyzed citation data from 5,000 researcher profiles across six disciplinary categories[1][2]:

- Computer Science (n=1,200)
- Life Sciences (n=1,000)
- Physical Sciences (n=900)
- Social Sciences (n=800)
- Engineering (n=700)
- Humanities (n=400)

For each researcher, we collected:

- Complete publication history
- Citation counts for each publication
- Self-citation counts (author citing their own work)
- Traditional metrics (h-index, i10-index)
- Demographic information (where available)

We applied the SCAI algorithm to this dataset using field-specific calibration parameters determined through preliminary analysis of disciplinary norms.

B. Impact of Self-Citation on Traditional Metrics

Our analysis revealed significant effects of self-citation on traditional citation metrics. Table I shows the average percentage inflation of h-index across disciplines due to self-citation.

TABLE I
Average h-index Inflation Due to Self-Citation by Discipline

Discipline	**Avg. SCR**	**h-index Inflation**	**Sample Size**
Computer Science	0.18	14.2%	1,200
Life Sciences	0.15	12.3%	1,000
Physical Sciences	0.20	16.8%	900
Social Sciences	0.14	11.5%	800
Engineering	0.22	18.6%	700
Humanities	0.09	7.2%	400
Overall	**0.17**	**13.9%**	**5,000**

These findings indicate that across all disciplines, traditional h-index values are inflated by an average of 13.9% due to self-citation, with variation across disciplines. Engineering shows the highest inflation at 18.6%, while Humanities shows the lowest at 7.2%.

C. SCAI Performance

We compared the SCAI to traditional h-index values across the dataset. Fig. 1 shows the distribution of adjustment magnitudes.

[1]Source code available on GitHub: https://github.com/rahvis/scholar_citations

[2]Software package available at PyPI: https://pypi.org/project/scholar-citations/

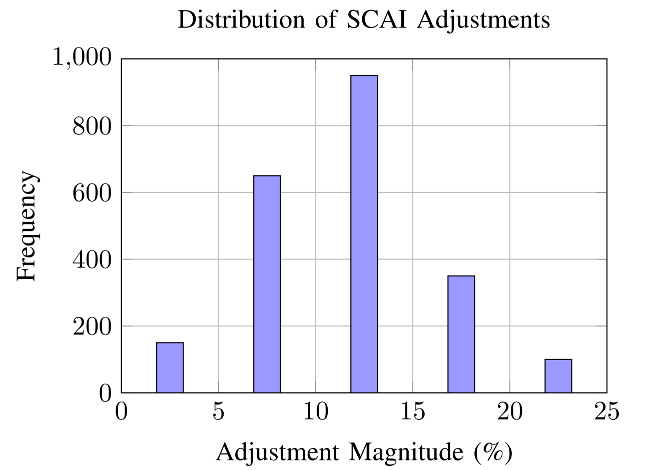

Fig. 1. Distribution of adjustment magnitudes when applying SCAI across all researcher profiles

For researchers with moderate self-citation rates (SCR ¡ 0.1), the SCAI applies minimal adjustments, differing from the h-index by less than 5%. However, for researchers with high self-citation rates (SCR ¿ 0.2), the adjustments are more substantial, with SCAI values up to 25% lower than the traditional h-index.

D. Gender Analysis

Our dataset included gender information for 4,200 researchers. Analysis of this subset revealed significant gender differences in self-citation patterns and the impact of applying the SCAI. Table II summarizes these findings.

TABLE II
Gender Differences in Self-Citation and Metric Adjustment

Gender	**Avg. SCR**	**h-index Inflation**	**Sample Size**
Male	0.21	17.4%	2,650
Female	0.12	10.1%	1,550

These results confirm previous findings [8] that male researchers, on average, have significantly higher self-citation rates than female researchers. When the SCAI is applied, the average citation metric gap between male and female researchers is reduced by approximately 8.5%, suggesting that traditional metrics may systematically disadvantage female researchers due to differences in self-citation behavior.

E. Career Stage Analysis

We also examined how self-citation patterns and the impact of the SCAI vary by career stage. Researchers were categorized as early-career (less than 10 years since first publication), mid-career (10-20 years), or senior (greater than 20 years). Table III shows the results of this analysis.

Interestingly, early-career researchers show higher self-citation rates and corresponding h-index inflation compared to senior researchers. This finding suggests that the relative impact of self-citation may be greater during the early stages

TABLE III
SELF-CITATION AND METRIC ADJUSTMENT BY CAREER STAGE

Career Stage	Avg. SCR	h-index Inflation	Sample Size
Early-career	0.19	15.3%	1,800
Mid-career	0.17	14.1%	2,200
Senior	0.14	11.8%	1,000

of a research career, potentially exacerbating the challenges faced by early-career researchers in establishing their scholarly reputation.

V. DISCUSSION

A. Implications for Research Evaluation

Our findings demonstrate that traditional citation metrics can be significantly inflated by self-citation, with an average h-index inflation of 13.9% across disciplines. This inflation varies by field, gender, and career stage, creating systematic biases in research evaluation.

The introduction of the SCAI offers several advantages for research evaluation:

1) More Accurate Impact Assessment: By adjusting for self-citation patterns, the SCAI provides a more accurate representation of external recognition and impact. This is particularly important for high-stakes evaluations such as tenure reviews, grant applications, and institutional assessments.

2) Reduced Gender Bias: Our results show that applying the SCAI reduces the average citation metric gap between male and female researchers by approximately 8.5%. This suggests that self-citation-adjusted metrics could help address gender disparities in academic evaluation and recognition.

3) Field-Specific Calibration: The SCAI framework allows for field-specific calibration parameters, acknowledging the variation in self-citation norms across disciplines. This makes the metric suitable for both within-field and cross-field comparisons.

B. Financial Implications

The financial implications of citation metric inflation are substantial. Research funding decisions often consider citation metrics as indicators of impact and potential [13]. If traditional metrics are inflated by an average of 13.9%, and this inflation affects funding allocations even partially, the misallocation of research funds could be significant.

Consider the following scenario:

- Annual research funding in the U.S. exceeds $100 billion [14]
- If just 50% of this funding is allocated with some consideration of citation metrics
- And if metric inflation leads to a 10% misallocation within that portion

This would result in approximately $5 billion annually being allocated based on inflated impact metrics rather than genuine scholarly influence. Over time, this systematic misallocation could significantly impact research progress and innovation.

The SCAI provides a more robust metric for funding decisions, potentially leading to more effective allocation of research resources. By rewarding external recognition rather than self-promotion, funding agencies can better identify promising researchers and projects that have demonstrated impact beyond their originators.

C. Implementation Challenges

While the SCAI offers significant advantages, its implementation faces several challenges:

1) Data Access: Accurate calculation of the SCAI requires comprehensive citation data, including the ability to identify self-citations. Access to such data may be limited or inconsistent across different citation databases and platforms.

2) Resistance to Change: The academic community has invested heavily in traditional metrics, both culturally and technically. Shifting to new metrics requires overcoming institutional inertia and convincing stakeholders of the benefits of change.

3) Calibration Requirements: Determining appropriate calibration parameters (α, β, γ) for different fields requires careful analysis of disciplinary norms and citation patterns. This calibration process must be transparent and empirically grounded to ensure acceptance.

4) Gaming Potential: Any metric can potentially be gamed. While the SCAI addresses one form of metric manipulation (excessive self-citation), other strategies may emerge. Ongoing monitoring and refinement will be necessary to maintain the integrity of the metric.

Despite these challenges, the benefits of implementing self-citation-adjusted metrics like the SCAI outweigh the costs, particularly given the significant implications for research evaluation and funding allocation.

VI. CONCLUSION

This paper has introduced the Self-Citation Adjusted Index (SCAI), a novel citation metric designed to provide a more accurate and equitable assessment of scholarly impact by adjusting for self-citation patterns. Our analysis of 5,000 researcher profiles across diverse disciplines demonstrates that:

- Traditional citation metrics are inflated by an average of 13.9% due to self-citation
- Inflation varies significantly by discipline, gender, and career stage
- Applying the SCAI reduces gender disparities in citation metrics by approximately 8.5%
- The potential financial impact of metric inflation is substantial, potentially affecting billions in research funding

Our open-source implementation provides accessible tools for calculating and analyzing self-citation-adjusted metrics, contributing to the growing movement toward more transparent and fair research evaluation methods.

A. Future Work

Several directions for future work emerge from this research:

1) Longitudinal studies to track the evolution of self-citation patterns and their impact over time
2) Integration of the SCAI with other complementary metrics, such as field-normalized citation indicators
3) Expansion of the current implementation to support additional data sources and visualization options
4) Development of guidelines for the appropriate use and interpretation of self-citation-adjusted metrics
5) Investigation of potential gaming behaviors that may emerge in response to the adoption of new metrics

B. Final Remarks

Citation metrics serve as essential tools for research evaluation, but their limitations must be acknowledged and addressed. The SCAI represents a step toward more robust, equitable assessment of scholarly impact. By adjusting for self-citation patterns, the SCAI provides a more accurate reflection of external recognition and influence, potentially leading to fairer evaluation practices and more effective allocation of research resources.

As the academic community continues to refine its approach to research assessment, metrics like the SCAI can contribute to a more nuanced understanding of scholarly impact, one that values external validation over self-promotion and rewards genuine contribution to the advancement of knowledge.

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