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Rescaling the disruption index reveals the universality of disruption distributions in science

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Abstract
Encompassing an intricately profound propensity for revolutionary, paradigm-shifting ramifications and the potential to wield an irrefutably disruptive sway on forthcoming research endeavors, the notion of the Disruption Index (*DI*) has surfaced as an object of fervent scientific scrutiny within the realm of scientometrics. Nevertheless, its implementation faces multifaceted constraints. Through a meticulous inquiry, we methodically dissect the limitations of *DI*, encompassing: (a) susceptibility to variations in reference numbers, (b) vulnerability to intentional author manipulations, (c) heterogeneous manifestations across diverse subject fields, (d) disparities across publication years, (e) misalignment with established scientific impact measures, (f) inadequacy in convergent validity with expert-selected milestones, and (g) a prevalent concentration around zero in its distribution. Unveiling the root causes of these challenges, we propose a viable solution encapsulated in the Rescaled Disruption Index (*RDI*), achieved through comprehensive rescaling across fields, years, and references. Our empirical investigations unequivocally demonstrate the efficacy of *RDI*, unveiling the universal nature of disruption distributions in science. This introduces a robust and refined framework for assessing disruptive potential in the scientific landscape while preserving the core principles of the index.

Keywords Science of science · Scientometrics · Rescaled disruption Index · Scientific impact

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Introduction

The realm of science is a multifaceted and intricate domain, characterized by its intrinsic complexity and vast interconnections (Myers, 2020; Price, 1965; Wang & Barabási, 2021; Wang et al., 2013; Yin et al., 2022). In our quest to unravel the inner workings of the scientific enterprise, we employ quantitative metrics dedicated to the assessment and evaluation of scientific output (Gao et al., 2019; Wang et al., 2013; Zeng et al., 2017). For an extended period, citation-based metrics have held sway as the predominant yardstick within the realm of scientometrics. These metrics, encompassing measures such as citation count (Waltman, 2016), the h-index (Hirsch, 2005), and the Impact Factor (Garfield & Sher, 1963), have played a pivotal role in illuminating the extent of influence and recognition garnered by scientific papers and researchers. However, citation-based metrics are primarily adept at delineating the extent to which a scientific work has influenced subsequent research, providing only a scant glimpse into the underlying innovative potential and novel contributions encapsulated within the work itself (Fortunato et al., 2018; Hicks et al., 2015). This inherent deficiency within traditional metrics has spurred a quest for more nuanced and sophisticated approaches capable of shedding light on the innovative dimensions of scientific endeavors (Wu et al., 2022). Fortuitously, in the past decade, a burgeoning body of scholarship has emerged to address this gap in our understanding by proffering innovative perspectives on the measurement of scientific innovation through the lens of citation networks (Shibayama & Wang, 2020; Uzzi et al., 2013; Wang et al., 2017). Among these pioneering efforts, one prominent and influential framework stands out—the *DI*—conceived by Funk and Owen Smith in their seminal work published in 2017.

The DI represents a watershed in the evolution of scientometric tools, as it endeavors to quantify not just the influence but also the disruptive potential of scientific contributions (Park et al., 2023; Wu et al., 2019). The *DI* endeavors to uncover the extent to which a scientific work has the potential to disrupt prevailing paradigms and catalyze transformative change within its respective field (Azoulay, 2019). In essence, the *DI* recognizes that true innovation lies not solely in the extent of citations a work accrues but also in its capacity to challenge and reshape existing knowledge paradigms (Leydesdorff & Bornmann, 2021). This novel approach to scientometrics opens up a vista of possibilities for assessing and nurturing innovation within the scientific community, by providing a more comprehensive and nuanced understanding of the transformative potential inherent in scientific contributions (Yang, et al., 2023c). The *DI* reflects a growing awareness within the scientific community of the need to move beyond conventional measures of impact and delve deeper into the realm of innovation, where the true potential for scientific advancement lies. As we continue to explore and refine these advanced scientometric tools, we stand poised to gain a richer, more holistic understanding of the multifaceted world of science and its potential to disrupt and reshape the boundaries of human knowledge (Liu et al., 2023).

Notwithstanding, recent investigations have brought to light the incongruities and constraints associated with the *DI* (Bornmann & Tekles, 2021; Bornmann et al., 2020a, 2020b; Leydesdorff & Bornmann, 2021; Ruan et al., 2021; Yang et al., 2023b). Wang et al. (2022) uncovered that numerous scientific works boasting high *DI* values did not entail groundbreaking research. In a similar vein, Ruan et al. (2021) argued that the *DI* exhibits inconsistencies across different fields and citation databases. Our preliminary studies (Yang et al., 2023a, b) have also highlighted that *DI* could be manipulated by authors, as papers with fewer reference counts can yield significantly higher *DI* scores. Due to its simple formula, *DI* is susceptible to various influences, rendering not all publications with elevated *DI* values as truly

pioneering achievements (Leydesdorff & Bornmann, 2021). Consequently, the utilization of *DI* for assessing innovation and evaluation may prove unsuitable (Leydesdorff et al., 2021). Our earlier endeavors (Yang et al., 2023a, c) introduced the 2-step *DI* and Global *DI*, incorporating higher citation generations. Regrettably, these methods primarily added complexity to the formula without effectively addressing *DI*'s limitations.

Undoubtedly, the quest for an improved approach to enhance the *DI* holds paramount importance, as its accurate and precise measurement of scientific innovation and paradigm-shifting capacity remains essential. In this study, through empirical investigation, we meticulously delineate all conceivable limitations of *DI*. To address them, we amalgamate existing insights from the science of science regarding disruption (Leydesdorff & Bornmann, 2021; Park et al., 2023; Yang et al., 2023a) and normalization methods (Radicchi & Castellano, 2011; Radicchi et al., 2008; Waltman & van Eck, 2013, 2015), presenting the *DI*, achieved through steadfast rescaling of *DI* on three distinct levels. The proposed *RDI* not only offers a novel and straightforward approach but also proves to be effective and feasible in ameliorating the aforementioned predicaments while preserving the foundation of its rationales. Most notably, it unveils pattern in disruption distributions within science.

In light of these considerations, this paper embarks on a comprehensive exploration of critical research questions that underpin the overarching objectives of this study:

(RQ1) What are the inherent limitations of the *DI* and their underlying causes?
(RQ2) How can rescaling the *DI* ensure consistency in distribution and improve assessment efficacy?
(RQ3) Does the implementation of the *RDI* effectively unveil the universal nature of disruption distributions?

Through a rigorous examination of the proposed research questions, this paper aspires to yield profound contributions to the field of scientometrics. By elucidating the intricacies of disruptive potential and proposing a rescaling methodology, this study advances our theoretical comprehension of scientific innovation and paradigm shifts. The ultimate goal is to pave the way for more comprehensive and reliable assessments of research impact within the academic landscape, benefitting researchers, institutions, and policymakers alike.

The remainder of this paper unfolds as follows: Sect. "Background and data" offers crucial background information, elucidating the theoretical underpinnings of the *DI* and outlining the dataset used for this investigation. Sect. "Limitations of disruption index (*DI*)" presents a quantitative synthesis, analysis, and discussion of the limitations inherent in *DI*, unraveling their intricacies. Sect. "Rescaled disruption index (*RDI*)" delves into the fundamental causes of these limitations, culminating in the proposition of the *DI* and providing a comprehensive breakdown of each normalization step. sect. "Universality of disruption distributions" effectively demonstrates the prowess of *RDI*, exhibiting its capacity to reveal the universal patterns characterizing disruption distributions. Sect. "Discussion" engages in further discourse, encompassing the applications and limitations of *RDI*, along with a forward-looking perspective on potential avenues for extended exploration and refinement.

Background and data

Rationales of disruption index (*DI*)

In the realm of scientific advancement, it is widely acknowledged that the genesis of novel knowledge is inextricably intertwined with the reservoir of preexisting wisdom—a principle elegantly encapsulated by the metaphorical imagery of 'standing on the shoulders of giants' (Betancourt et al., 2023; Jo et al., 2022). In this context, the term 'disruption' assumes profound significance, denoting a transformative shift of paradigmatic magnitude. This transformative concept alludes to the emergence of entities that, at their core, deviate fundamentally from the preceding state of affairs (Arthur, 2007, 2009; Mokyr, 1990). For instance, Albert Einstein's theory of relativity (Einstein, 1916) revolutionized the traditional scientific framework, while the discovery of the double helix structure of DNA by Watson and Crick (1953) fundamentally reshaped our understanding of life's nature, akin to how the BTW model (Bak et al., 1987) portends to introduce groundbreaking technologies to the field of physics.

All the aforementioned seminal works have successfully upended established paradigms and proffered new ones in their stead. This exemplifies the essence of disruption within the realm of science (Park et al., 2023; Wu et al., 2019). The intellectual lineage of the concept of disruption can be traced back to the seminal work of Thomas Kuhn (1962), whose scholarly contributions resonate profoundly with the notion of challenging and transcending established paradigms as a cornerstone of scientific progress. This intellectual resonance elegantly converges with the contemporary concept of disruptive innovation, as elucidated by Bower (1995). The crux of this perspective lies in the assertion that scientific progress often germinates from anomalies that defy prevailing paradigms, and transformative breakthroughs manifest through the application of fresh ideas or innovative methodologies aimed at resolving these enigmatic anomalies (Lin et al., 2022). The phenomenon of disruptive science is not to be underestimated, for it possesses the inherent capacity to radically alter the fortunes of organizations and entire industries (Fontana et al., 2020; Mariani et al., 2016). This assertion leads us to the imperative question of how one might quantitatively assess the disruptive nature of scientific knowledge. A rigorous examination of the intricate web of interconnections within the scientific landscape is indispensable, given that disruptive papers are frequently characterized as representing "punctuated advances beyond previous theory, methods, or findings", (Bornmann et al., 2020b).

Acknowledging the pressing need for robust metrics to appraise research innovation within the scientific domain, Funk and Owen Smith introduced the *DI* in 2017. This pioneering approach leverages the intricate local citation structures as its analytical foundation to evaluate the novelty of research and its latent potential to catalyze transformative innovation. By scrutinizing the intricate tapestry of the citation network at a localized level, it deftly navigates the complex interplay between preceding and subsequent generations of research, all while meticulously accounting for the dynamic evolutionary forces and pivotal transitions that define the landscape of scientific publications (Yang et al., 2023a, c). This approach is rooted in underscoring the paramount importance of acknowledging and interpreting the evolutionary dynamics that shape the landscape of scientific knowledge dissemination (Leydesdorff & Bornmann, 2021). Illustrated in Fig. 1, the *DI* is represented by the following formula:

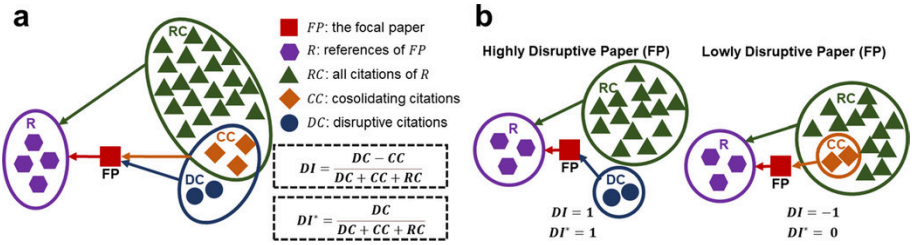


Fig. 1 Rationale and Formula of the *DI*. **a** The citation network and parameters of *DI*, including FP, *R*, *RC*, *CC*, and *DC*. **b** Examples of the citation network of highly disruptive papers and lowly consolidating papers

$$DI = \frac{DC - CC}{DC + CC + RC} \tag{1}$$

where *CC* (consolidating citations) signifies the number of publications referencing both the focal paper (FP) and its sources, *DC* (disruptive citations) represents the count of publications citing FP without referencing its cited sources, and *RC* denotes the count of publications citing FP's sources without referencing FP itself. The *DI* scrutinizes the interplay between these citation patterns to gauge the extent of disruption.

A focal paper that references sources also cited by many of the papers citing FP (resulting in a lower *DI*) is seen as contributing to the consolidation of the existing paradigm, aligning with and reinforcing established knowledge. Conversely, when future citations of the focal paper neglect to acknowledge the sources cited by FP (resulting in a higher *DI*), it signals the potential disruption of the research paradigm, possibly ushering in new fields and a reconfiguration of existing knowledge boundaries (Yang et al., 2023b). Papers with lower *DI* values are heralded as highly disruptive, representing contributions that push the boundaries of established paradigms, while higher values indicate papers that strengthen and uphold the existing research paradigm within their respective fields. By employing the *DI*, researchers gain the means to assess the disruptive potential of scientific research, yielding valuable insights into knowledge creation and paradigm shifts in science.

Data

In this paper, we embark on a quantitative analysis to comprehensively explore the rationales, limitations, causes, and potential remedies of the *DI*. To facilitate our investigation, we introduce the pertinent data at the outset. Our study draws on citation data provided by the American Physical Society (APS). To ensure the robustness of our analysis, we narrow our focus to publications predating the year 2010, specifically selecting papers with at least one PACS code and one reference. As a result, we extract a well-defined subset of the APS dataset, amounting to 315,982 papers. The rationale behind this time-bound selection is twofold: to retain an adequate number of citation windows for accurate assessments (Bornmann & Tekles, 2019) and to mitigate potential confounding factors arising from changes in citation behaviors or publication patterns over time (Zeng et al., 2017).

To categorize papers effectively, we implement the Physics and Astronomy Classification Scheme (PACS), which allocates papers to distinct fields based on their first digital PACS codes. As depicted in Appendix Table 1, we meticulously classify all papers into ten subject fields using this scheme.

To ascertain a set of expert-selected landmark papers in the realm of Physics, we adhere to a rigorous selection process (Yang et al., 2023d). Our approach involves tapping into multiple reputable sources. Initially, we utilize a dataset encompassing Nobel Prize-winning papers, sourced from Li et al. (2019), which covers Nobel Prize recipients in the natural sciences. Additionally, we incorporate milestone papers from Physical Review journals, specially curated for the momentous 125th anniversary celebration in 2018. Furthermore, we include milestone papers from Physical Review Letters, spanning the period from 1959 to 2001. Lastly, we incorporate milestone papers from Physical Review E (Please refer to the Data Availability for these data links). Altogether, our meticulous curation yields a compilation of 72 landmark papers included in our data, paving the way for comprehensive analyses in the pursuit of refining the *DI*.

Limitations of *DI*

The imperative pursuit of an enhanced approach to augment the *DI* stems from its pivotal role in accurately and precisely measuring scientific innovation and the capacity for paradigm-shifting within the academic landscape. While prior research has acknowledged the limitations of *DI*, a comprehensive and systematic summarization of these constraints backed by robust evidence is still lacking (Bornmann & Tekles, 2021; Bornmann et al., 2020a, 2020b; Deng & Zeng, 2023; Leibel & Bornmann, 2023; Leydesdorff & Bornmann, 2021; Ruan et al., 2021). Consequently, in this study, we undertake empirical investigations utilizing our dataset, wherein we meticulously delineate seven conceivable issues of *DI*, as depicted in Fig. 2, and discussed in detail below.

Susceptibility to variations in reference numbers

As demonstrated in Fig. 2a, we segregate papers into four groups based on their reference numbers and illustrate their respective distributions. The one-way ANOVA test indicates significant differences between these groups ($p < 0.001$), revealing the highly susceptible nature of *DI* to variations in reference numbers. Papers with lower reference counts exhibit elevated standard deviations and mean values of DI, whereas papers with higher reference counts generally yield *DI* values below 0 (negative).

Susceptibility to manipulations by authors

Authors can manipulate the *DI* of their papers by just adding fewer references (Yang et al., 2023c). Figure 2b illustrates the negative correlation between *DI* and reference number, with an Ordinary Least Squares (OLS) regression analysis yielding a significantly negative coefficient ($coef = -4.9$, $p < 0.001$). This result underscores how authors can manipulate the disruption of their papers by intentionally citing fewer sources, providing evidence for issue (1) wherein papers with more references tend to have lower *DI* values.

Heterogeneity across diverse subject fields

Employing the first-level PACS codes, we classify papers into ten subject fields. Figure 2c showcases the analysis and comparison of *DI* distributions in different fields,

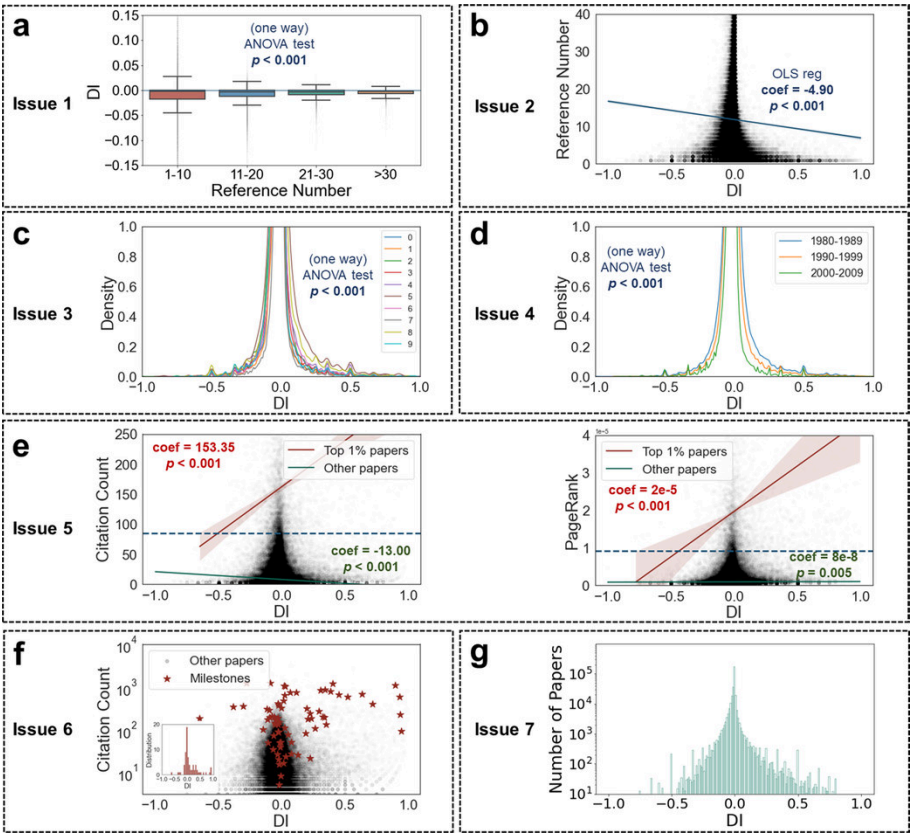


Fig. 2 Limitations of the *DI*. **a** Distributions of *DI* for binned reference numbers. **b** Correlation between reference numbers and *DI*. **c** Kernel Density Estimation (KDE) of *DI* for different subject fields. **d** KDE of *DI* for different publication year periods. **e** Correlation between scientific impact metrics and *DI*, for top 1% high impact papers and other papers, respectively. **f** Distribution of expert-selected milestone papers. **g** Distribution of *DI* in APS dataset. Shaded areas for regression lines indicate 95% confidence intervals

revealing significant heterogeneity (ANOVA test, $p < 0.001$). This observed heterogeneity is challenging to explain; for instance, papers in Field 5 (Physics of Gases, Plasmas, and Electric Discharges) appear to be more disruptive when *DI* values are above 0 (brown line on the right) and less disruptive when *DI* values are below 0 (brown line on the right).

Disparities across different publication years

By grouping publication years into three periods (Fig. 2d) and comparing *DI* distributions across these periods (ANOVA test, $p < 0.001$) reveal significant heterogeneity. Similar to issue (3), this observed heterogeneity is perplexing, with papers published in the 1980s displaying either heightened disruption when *DI* values are above 0 (brown line on the right) or reduced disruption when *DI* values are below 0 (brown line on the right).

Incompatibility with scientific impact metrics

Evaluating the correlation between the *DI* and established citation-based scientific impact metrics, we primarily use citation count and PageRank for comparison (Fig. 2e). What becomes apparent is that, while scientific impact metrics exhibit significant positive correlations with *DI* for the top 1% highly cited papers, the same does not hold true for the rest of the papers, where coefficients turn negative. This disparity underscores the inconsistency between *DI* and traditional scientific impact metrics. This finding remains consistent even when a threshold of at least 10 citations is used (see Appendix Fig. 6).

Inadequacy in convergent validity with expert-selected papers

Analyzing the distributions of expert-selected milestone papers reveals that, while most milestone papers boast very high citation counts (Fig. 2f), a considerable number of them possess *DI* distributed around zero. This lack of convergent validity raises concerns about the efficacy of using *DI* to select milestone papers.

Concentration around zero in distribution

Figure 2g highlights a clear concentration of *DI* around zero for the majority of papers. In fact, in our sample dataset, the average *DI* value is − 0.01, with a standard deviation of a mere 0.06 (see Appendix Table 2). This concentration makes it exceptionally challenging to distinguish which papers are genuinely more disruptive within such a tightly clustered distribution. Moreover, while categorizing papers into either disruptive or consolidating, an expectation arises that only a few papers would fall into the disruptive category, and the majority would consolidate existing knowledge (Bu et al., 2021; Wu et al., 2019). However, the *DI* distribution indicates that only a minority of papers fit into either disruptive or consolidating categories, leaving the majority with DI values close to 0, which complicates defining their nature. It appears that beyond disruption and consolidation, a third dimension eludes characterization, leaving an ambiguity in defining the majority of papers.

While the effect size of heterogeneity across varying reference counts, publication years, and fields appears modest (ω^2 slightly above 0.01 for ANOVA tests, refer to "Appendix" for elaboration), significant *p*-values and subsequent pairwise witch's T tests (see Appendix Fig. 7) underscore the inconsistency of *DI* across these parameters. It's paramount to recognize that the limitations of *DI* extend beyond these seven constraints, and many of the limitations and proposed solutions for *DI* may have common underlying reasons. For instance, there have been suggestions to introduce a threshold, such as including only papers with at least 10 citations and 10 cited references in the calculation of *DI* scores (Leibel & Bornmann, 2023; Ruan et al., 2021; Sheng et al., 2023). This is because *DI* faces difficulties in comparing papers with high or low references and citations. To address these limitations effectively, it is crucial to uncover the underlying causes and factors responsible for these constraints. These underlying factors will be the focus of our upcoming discussion in the subsequent section.

Rescaled disruption index (*RDI*)

To gain a comprehensive understanding of the *DI* and delve into its rationales and limitations quantitatively, let us closely examine the three key parameters of *DI*, namely, *DC* (disruptive citations), *CC* (consolidating citations), and *RC* (other citations to the references of FP). Notably, *DC*+*CC* represents the total citations of FP, indicating that *DC* and *CC* account for distinct fractions of the total citations, respectively. Previous research, including our early works (Yang et al., 2023b), has demonstrated that *DC* itself can effectively capture the disruptive impact of papers, while *CC* tends to function more like "citation foam", displaying limited correlation with success. Furthermore, Leydesdorff et al. (2021) and Chen et al. (2021) also contend that the numerator of *DI* (*DC*—*CC*) involves a repeat subtraction of *CC* from the total citations, thereby leading to the introduction of a new index, *DI**, defined as:

$$DI^* = \frac{DC}{DC + CC + RC} \tag{2}$$

While *DI** appears promising by employing *DC* as the numerator, we seek to explore additional factors that potentially contribute to the limitations of *DI*. Focusing on the denominator of *DI*, *DC*+*CC*+*RC*, we recognize that *DC*+*CC* equals the total citations of FP, yet the parameter *RC* has been relatively overlooked in scholarly discourse. Nevertheless, we posit that *RC* constitutes a key factor influencing the clustering distributions, inconsistency, and lack of convergent validity observed in *DI*.

Upon examining the distribution of *RC* and its relationship with the number of references in FP, a noticeable pattern emerges. Data in Fig. 3b reveals a clustering of *RC* values predominantly on the left side, and this is clearly illustrated by the steep regression line. The regression coefficient for *RC*, standing at a substantial 62.55 ($p < 0.001$), signifies that, on average, the inclusion of a single additional reference results in a 62.55 unit increase in the *RC* value.

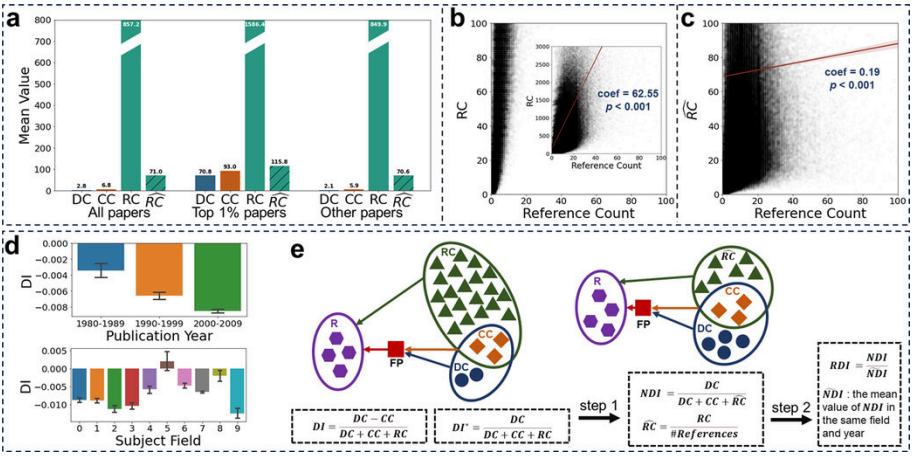


Fig. 3 Causes of limitations and the proposal of the *DI*. **a** Mean values and standard errors of *DC*, *CC*, *RC*, and $\widehat{RC}$ for top 1% high impact papers and other papers, respectively. **b** Correlation between reference count and *RC*. **c** Correlation between reference count and $\widehat{RC}$. **d** Distribution of *DI* in different years and fields. **e** Steps of the proposal of *RDI*. Shaded areas for regression lines and error bars indicate 95% confidence intervals

While *RC* is intended to represent the related knowledge of FP, this substantial effect has a noteworthy consequence. It leads to *DI* values that hover very close to zero for the majority of papers, rendering the comparison of *DC* and *CC* essentially invalid in many contexts (Ruan et al., 2021).

Hence, it becomes imperative to implement a rescaling strategy for *RC*. Given that *RC* quantifies the total number of papers citing the references within FP (excluding citations to FP itself), an approach to address this concern is to replace the total number of papers citing FP's references with the average number of papers citing those references (Yang et al., 2023c). This normalization process helps mitigate the skewed influence of *RC*, creating a more balanced perspective for evaluating the disruptive potential of scientific papers. That is, dividing *RC* by the number of references of FP. In light of this, we propose the Normalized Disruption Index (*NDI*), which involves normalizing *RC* with FP's reference count:

$$NDI = \frac{DC}{DC + CC + \widehat{RC}} \tag{3}$$

$$\widehat{RC} = \frac{RC}{\#References} \tag{4}$$

where $\widehat{RC}$ represents the normalized *RC*. In Fig. 3c, we observe a very low coefficient (coef = 0.19) between reference count and $\widehat{RC}$. Additionally, Fig. 3a demonstrates that *RC* exhibits a significantly higher order of magnitude than *DC* and *CC* for all papers, whereas $\widehat{RC}$ does not, particularly for top-cited papers, where they nearly attain similar average values.

The final concern pertains to the uneven distribution of *DI* across different subject fields and publication year periods (see Fig. 3d), representing a heterogeneity that poses challenges for understanding and explanation. To address this issue, further normalization of *NDI* across fields and years becomes necessary. In this endeavor, we draw upon existing insights from the science of science regarding normalization methods (Radicchi & Castellano, 2011; Radicchi et al., 2008; Waltman & van Eck, 2013, 2015). This leads us to the introduction of the *DI*, which employs a two-level normalization process involving fields and time:

$$RDI = \frac{NDI}{\widetilde{NDI}} \tag{5}$$

where $\widetilde{NDI}$ represents the average value of *NDI* for all papers in the same field and year. It is essential to note that one reason for using *DI** as the baseline instead of *DI* is due to the range of *DI** being [0,1], which facilitates further normalization, while the range of *DI* is [-1,1], rendering normalization more complex.

In conclusion, the resulting *RDI* incorporates a three-level normalization process, encompassing reference count, fields, and publication year, which serves as a promising avenue to address the limitations of *DI* and advance our understanding of the disruptive potential of scientific research within the academic landscape.

Universality of disruption distributions

The introduction of the *DI* represents the universality of disruption distributions in science, and show effectiveness when assessing the disruption of papers. In Appendix Table 2, we present descriptive statistics of *DI*, *DI**, and *RDI*, shedding light on the notable features of *RDI*. A noteworthy distinction of *RDI* is its expanded range, exclusively encompassing positive values, with a minimum of 0 and an impressive maximum of 122. Crucially, the top 1% cited papers exhibit an average *RDI* of 4.51, while the remaining papers settle at 0.97, emphasizing *RDI*'s efficacy in differentiating highly cited papers from others, surpassing the capabilities of *DI* in this aspect.

Further comprehensive analysis akin to Sect. "Limitations of DI" elucidates how *RDI* adeptly overcomes all *DI* limitations. Figure 4 offers the outcomes of this rigorous analysis. First, *RDI* demonstrates remarkable resilience to variations in reference numbers and intentional manipulations (Fig. 4a–b). The distribution of *RDI*, categorized by

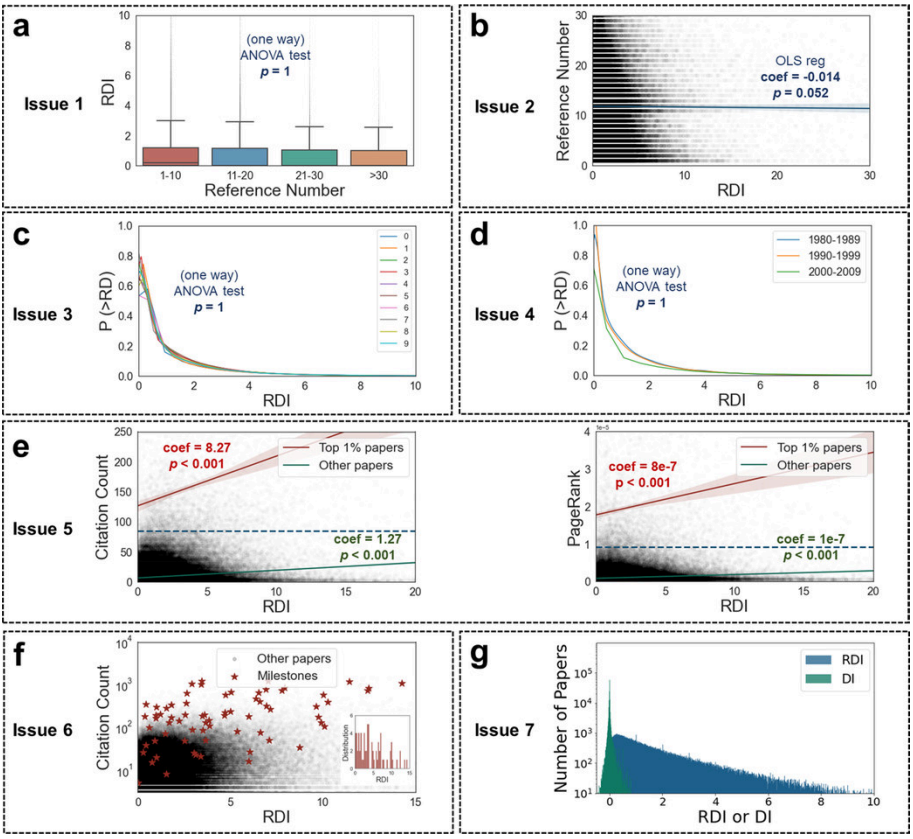


Fig. 4 The *DI* reveals the universality of disruption distributions. **a** Distributions of *RDI* for binned reference numbers. **b** Correlation between reference numbers and *RDI*. **c** Kernel density estimation (KDE) of *RDI* for different subject fields. **d** KDE of *RDI* for different publication year periods. **e** Correlation between scientific impact metrics and *RDI*, for top 1% high impact papers and other papers, respectively. **f** Distribution of expert-selected milestone papers. **g** Distribution of *DI* in APS dataset. Shaded areas for regression lines indicate 95% confidence intervals

reference numbers, exhibits consistent mean values and standard deviations, rendering it independent of reference count fluctuations. Moreover, the very low correlation coefficient ($coef = -0.014$, $p = 0.052$) provides compelling evidence for *RDI*'s minimal susceptibility to manipulations, reaffirming its robustness.

Second, *RDI* exhibits noteworthy consistency across diverse subject fields and publication years (Fig. 4c–d). The analysis and comparison of *RDI* distributions confirm remarkable homogeneity across different fields and publication years, facilitating direct assessments of paper disruptiveness while accounting for variations inherent in different academic domains and citation time frames.

Third, *RDI* demonstrates notable consistency with established scientific impact measures (Fig. 4e). It exhibits a highly positive correlation with citation-based impact metrics for both highly cited and normal papers, underscoring *RDI*'s alignment with recognized impact indicators. This alignment enhances its credibility and affirms its utility as a reliable assessment tool.

Fourth, *RDI* exhibits compelling convergent validity with expert-selected or milestone papers (Fig. 4f). An examination of the distributions of expert-selected milestone papers reveals that a majority of these papers garner significantly high citation counts, aligning with elevated *RDI* values. Notably, most milestone papers exhibit *RDI* values surpassing the median and mean values of *RDI*, solidifying its capacity to effectively select milestone papers and demonstrate robust convergent validity.

Fifth, *RDI*'s discernible distinction lies in its distribution, aligned with network science and the science of science (Barabási, 2016; Fortunato et al., 2018), specifically manifesting a power law distribution (Barabasi & Albert, 1999). Unlike *DI*, often centralized around zero with most papers lacking notable disruption or consolidation, *RDI*'s distribution unveils long-tail characteristics reminiscent of other citation-based metrics (Yang et al., 2023d). This characteristic fosters an impartial depiction of scholarly papers' disruptive potential. The *RDI* distribution in science distinctly illustrates that only a limited subset of papers exude disruption, while the majority contribute to consolidation.

A comprehensive comparison between milestone papers' *DI* and *RDI* values against average values within each year and field was conducted and presented in Fig. 5, revealing a striking trend. Remarkably, around half of the milestone papers' *DI* scores fall below the average values in select years and fields, indicating inconsistency in outperforming the average across all cases. In contrast, the majority of milestone papers' *RDI* scores surpass the average values, signifying a more consistent elevation beyond the norm. This observation provides compelling evidence that disparities in *DI* scores across fields and time periods are not solely reflective of research quality disparities within these categories. Instead, other confounding factors, effectively normalized through *RDI*, seem to influence these variations.

Taken together, the *DI* proficiently unveils the ubiquitous nature of disruption distributions while excelling in identifying highly cited papers and exhibiting robust convergent validity with expert-selected or milestone papers. The steadfast consistency of *RDI* across diverse subject fields and publication periods further fortifies its potential as a versatile and dependable metric for appraising the disruptive potential of scientific research within the academic landscape. Crucially, *RDI* retains the core rationales of the Disruption Index, positioning it as an authentic, valuable, effective, and indispensable framework for evaluating the extent of paradigm shifting in scholarly papers.

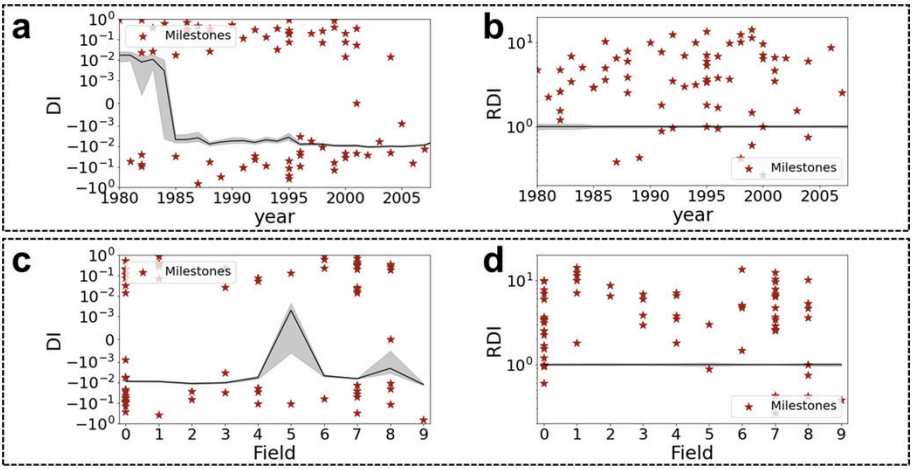


Fig. 5 Distributions of *DI* and *RDI* for milestone papers across year and fields. **a** Distributions of *DI* for milestone papers (red pentagrams) and all papers (black lines) in each year. **b** Distributions of *RDI* for milestone papers (red pentagrams) and all papers (black lines) in each year. **c** Distributions of *DI* for milestone papers (red pentagrams) and all papers (black lines) in each field. **d** Distributions of *RDI* for milestone papers (red pentagrams) and all papers (black lines) in each field. Shaded areas indicate 95% confidence intervals. (Color figure online)

Discussion

Applications

The *DI* offers a range of applications and some nuanced considerations. To begin with, *RDI* is designed to evaluate the most disruptive papers within their respective fields and years, akin to the concept of "hit papers" (Mukherjee et al., 2017) and rescaled citation metrics (Fortunato et al., 2018; Radicchi & Castellano, 2011; Radicchi et al., 2008). *RDI*'s capacity to do this obviates the need for fixed effects related to fields and years in regression models, simplifying the comparison of papers across various disciplines and time periods. This makes it an invaluable tool for pinpointing groundbreaking contributions.

In contrast to the *DI*, which may be more suited to specific contexts, such as particular academic fields or time frames, or requires the application of thresholds to focus on papers with higher reference counts and citations (Leibel & Bornmann, 2023; Ruan et al., 2021; Sheng et al., 2023), our approach aims to provide a means for assessing disruptive potential across a wide range of research papers. In doing so, *RDI* effectively eliminates the need for arbitrary thresholds and streamlines the process of evaluating the disruptive capacity of papers. This broader applicability underscores RDI's utility in multidisciplinary research contexts, where assessing disruptive contributions can be particularly challenging, and where the necessity for a versatile metric becomes evident.

One constraint of *RDI* is its inability to reveal trends over time and the heterogeneity across fields, given that *RDI* is rescaled for each year and field. As such, it may not capture existing trends indicating that papers are becoming less disruptive over time (Park et al., 2023) or that certain fields exhibit more disruptive characteristics than others

(Chu & Evans, 2021). The inherent differences in the qualities or patterns of papers in different years and fields are not explicitly considered. However, *RDI*'s primary goal is to offer an effective means of evaluating the level of disruption within different fields, making it a valuable tool for cross-sectional assessments. Nevertheless, an important strength of *RDI* lies in its ability to demonstrate the universality of disruption distributions across different fields and years. Our findings strongly validate *RDI* as an unbiased indicator of disruptive performance across disciplines and time periods, highlighting its potential to provide a consistent and objective assessment of research disruption. This objectivity makes *RDI* a valuable instrument for researchers and policymakers seeking to assess research impact with impartiality and accuracy.

Limitations

While the *DI* presents a promising framework that unveils the universal nature of disruption distributions, contributing significant insights to the field of scientometrics, it's paramount to acknowledge several limitations inherent in this study. Firstly, the empirical investigation primarily relies on the APS dataset, potentially constraining its representation of the entire scientific landscape across diverse disciplines and publication venues. Variability in data sources, citation practices, and publishing trends could impact the generalizability of findings. While this paper meticulously addresses APS dataset limitations, a broader analysis encompassing multiple datasets and disciplines would enhance the comprehensive understanding of *RDI*'s limitations. Additionally, the reliance on subjective judgments in selecting milestone papers may introduce biases into the analysis, particularly concerning the convergent validity discussion.

Secondly, while the study demonstrates the effectiveness of *RDI* in addressing the limitations of *DI* within the dataset, the long-term validation and stability of *RDI*'s performance over time remain to be observed (Wang et al., 2019; Yin & Wang, 2017). As scientific disciplines and publication practices evolve, *RDI*'s applicability and effectiveness may require periodic reassessment to ensure its continued relevance. Besides, it is essential to acknowledge that while *RDI* addresses several limitations of the original *DI*, the concept of disruptive potential itself remains multifaceted and challenging to precisely define (Funk & Owen-Smith, 2017; Park et al., 2023). Future research could explore alternative definitions or consider incorporating expert opinions to further refine the assessment of disruptive potential.

Thirdly, *RDI*'s framework does not explicitly account for variations in the disruptive nature across different years and fields. Early-stage sciences often exhibit higher disruptive tendencies (Park et al., 2023), while certain critical fields tend to foster more disruption (Chu & Evans, 2021). This heterogeneity remains unaddressed by *RDI*, which is crucial to note when employing it for evaluation purposes.

Fourthly, while the empirical investigation presented in this paper establishes valuable correlations and associations between *RDI* and various citation-related metrics, it is crucial to recognize that correlation does not necessarily imply causation (Wang & Barabási, 2021). Further experimental and causal inference studies might be warranted to establish a more robust causal relationship between *RDI* and disruptive potential. This could involve employing advanced statistical methods (Liu et al., 2023).

Lastly, the assessment of *RDI*'s performance in practical applications, such as evaluating scientists' impact and careers, assessing journal qualities, ranking universities, and informing funding decisions, is limited in this paper. Future research could delve deeper

into these practical applications to gauge the real-world implications and potential benefits of *RDI* in influencing decision-making processes in the scientific community and beyond.

Outlook

This study presents several promising directions for advancing the science of science and refining the assessment of disruptive potential in scientific research. Firstly, while the *DI* has demonstrated the universal nature of disruption distributions and provided a more nuanced assessment of disruptive impact, opportunities for refinement and enhancement persist. Future inquiries could delve deeper into the normalization process, exploring alternative normalization approaches to validate and fortify the robustness of *RDI*'s performance. Incorporating expert opinions and subjective judgments into the assessment of disruptive potential might augment *RDI*'s precision and comprehensiveness further.

Secondly, applying *RDI* across diverse datasets and scientific disciplines offers an avenue for cross-disciplinary comparisons and insights. Expanding the analysis to multiple datasets and subject fields would enable a more comprehensive evaluation of *RDI*'s efficacy and broaden its applicability in understanding disruptive potential across different domains. Additionally, studying *RDI*'s performance over extended periods and within dynamic research landscapes could elucidate its temporal stability and evolutionary trends.

Thirdly, investigating the synergies between *RDI* and emerging scientometric metrics could yield novel insights into capturing the intricate nature of disruptive research. Integrating *RDI* with network-based analyses, measures of novelty (Uzzi et al., 2013), co-citation methodologies, or Altmetrics could potentially augment its efficacy and accuracy in detecting paradigm shifts and transformative contributions.

Appendix

Statistical methods and effect size measures

The one-way ANOVA test served as a vehicle to uncover variations in the *DI* across diverse categories, encompassing reference count, publication years, and subject fields. While the effect sizes, notably the omega squared (ω^2), appeared relatively modest (0.009, 0.0176, and 0.0164 for Fig. 2a (issue 1), Fig. 2c (issue 3), and Fig. 2d (issue 4), respectively), the established threshold of an effect around 0.01 signifies a minor effect (Cohen, 2013). Despite these modest effect sizes, the derived significance from these analyses underscores consistent disparities in *DI* across reference count, publication years, and fields. It's essential to note that effect size thresholds can vary, contingent upon the field of study, context, and specific research area (Cohen, 2013). Within the realm of *DI*, constrained by a limited range, mean, and standard deviation, even minute effect sizes bear significance. This significance is crucial, given the imperative for statistically consistent quantitative evaluations of disruption.

Parallel to the one-way ANOVA, comprehensive pairwise comparisons via Witch's T tests (illustrated in Appendix Fig. 7) provided deeper insights into specific inter-group differences within each category. The resultant p-values accentuated varying levels of disruptive potential across discrete reference count categories, publication years, and subject fields. These tests corroborated the significance of the identified inconsistencies

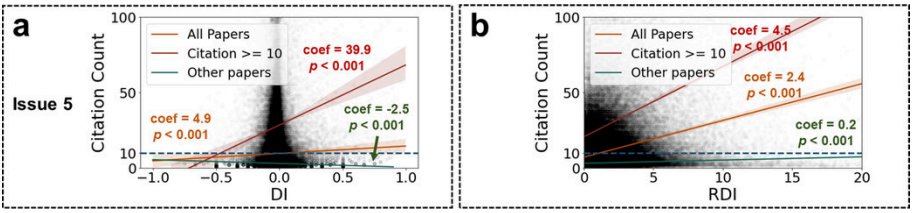


Fig. 6 Correlation between the citation count and *DI* and *RDI*, for all papers, papers with citation over 10, and other papers, respectively. Shaded areas for regression lines indicate 95% confidence intervals

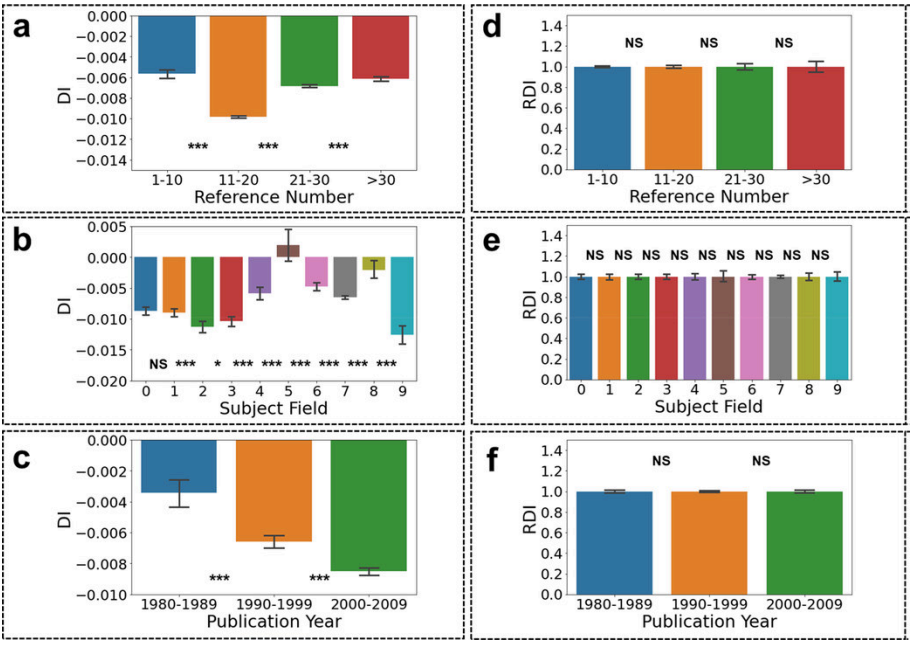


Fig. 7 The average values of *DI* and *RDI* across varying reference counts, publication years, and fields. Error bars indicate 95% confidence intervals. Two-tailed Witch's t tests were conducted for all adjacent pairs within the bar plot. $^{*}p<0.05$, $^{**}p<0.001$, $^{***}p<0.001$, NS $p\geq 0.05$

in *DI* across different categories, further fortifying the argument that *RDI* unveils the universal nature of disruption distributions in science.

Taken together, while the effect sizes indicating heterogeneity across categories may not be notably substantial, the emphasis remains on the discerned significant differences through meticulous statistical analyses. Despite their modest nature, these effect sizes shed light on the inconsistencies in *DI* across reference counts, publication years, and fields. When compared to the results obtained from *RDI*, these findings collectively underscore the role of rescaling the *DI* in elucidating the universality of disruption distributions in scientific research.

See Figs. 6 and 7 and Table 1 and 2.

Table 1 10 subject fields based on the first digital PACS codes

PACS	Subject fields in APS (Physics)
0	General
1	The physics of elementary particles and fields
2	Nuclear physics
3	Atomic and molecular physics
4	Electromagnetism, optics, acoustics, heat transfer, classical mechanics, and fluid dynamics
5	Physics of gases, plasmas, and electric discharges
6	Condensed matter: structural, mechanical and thermal properties
7	Condensed matter: electronic structure, electrical, magnetic, and optical properties
8	Interdisciplinary physics and related areas of science and technology
9	Geophysics, astronomy, and astrophysics

Table 2 Descriptive statistics of the metrics and parameters

Class	Metric	Obs	Mean	Std	Min	Median	Max
All papers	Reference	315,982	11.82	9.55	1	10.00	583
	Citation	315,982	9.55	24.49	0	4.00	3089
	DC	315,982	2.78	13.53	0	1.00	2398
	CC	315,982	6.77	15.02	0	3.00	2073
	RC	315,982	857.18	1412.19	0	401.00	31,899
	$\widehat{RC}$	315,982	71.03	112.71	0	38.19	5463
	DI	315,982	− 0.01	0.06	− 1	0.00	1
	DI*	315,982	0.02	0.06	0	0.00	1
	RDI	315,982	1.00	2.31	0	0.05	122
Top 1% papers	Reference	3109	16.23	26.28	1	11.00	583
	Citation	3109	163.84	153.25	86	122.00	3089
	DC	3109	70.82	108.13	0	45.00	2398
	CC	3109	93.02	87.14	0	80.00	2073
	RC	3109	1586.45	2111.74	1	975.00	31,899
	$\widehat{RC}$	3109	115.75	122.32	1	84.59	1934
	DI	3109	0.01	0.17	− 0.7	− 0.02	1
	DI*	3109	0.10	0.15	0	0.04	1
	RDI	3109	4.51	3.69	0	3.51	35
Other papers	Reference	312,873	11.78	9.22	1	10.00	448
	Citation	312,873	8.02	11.55	0	4.00	85
	DC	312,873	2.10	4.71	0	0.00	83
	CC	312,873	5.91	8.81	0	3.00	84
	RC	312,873	849.94	1401.59	0	397.00	16,602
	$\widehat{RC}$	312,873	70.59	112.52	0	37.88	5463
	DI	312,873	− 0.01	0.06	− 1	0.00	1
	DI*	312,873	0.01	0.05	0	0.00	1
	RDI	312,873	0.97	2.26	0	0.00	122

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Author contributions AJY: writing-original draft, conceptualization, methodology, software, data visualization, validation, data curation, resources. HG: writing- review and editing, supervision. YW: writing- review and editing, validation. CZ: writing- review and editing, validation. SD: writing-review and editing, supervision, funding acquisition.

Data availability The APS citation dataset is available at https://journals.aps.org/datasets. The Nobel-winning Papers and Laureates data used in this study are open-access at Harvard Dataverse https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/6NJ5RN. For milestone papers identified by the American Physical Society, please visit https://journals.aps.org/125years, https://journals.aps.org/prl/50years/milestones, and https://journals.aps.org/pre/collections/pre-milestones. Other data used in this study can be obtained by making reasonable requests.

Declarations

Conflict of interest The authors declare no competing interest relevant to this article.

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