Information Processing and Management 60 (2023) 103420



Contents lists available at ScienceDirect

Information Processing and Management

journal homepage: www.elsevier.com/locate/infoproman



From consolidation to disruption: A novel way to measure the impact of scientists and identify laureates

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ARTICLE INFO

Keywords:
Science of science
Citation network
Disruption
Consolidation
Scientist evaluation
Science Policy

ABSTRACT

This study proposes a novel approach for evaluating the impact of scientists by introducing a new set of metrics and a dual measurement framework that combines the concepts of disruption and consolidation. Traditional metrics like total citation and h-index are limited in their ability to capture the full range of a scientist's influence, and therefore the Scientists' Disruptive Citation (SDC), Disruptive h-index (D h-index), and consolidating metrics are introduced to provide a more comprehensive evaluation of scientists' disruptive and consolidating influence. Using a dataset of 463,348 papers, 234,086 disambiguated scientists, and data on three important awards, including Nobel Prize, Wolf Prize, and Dirac Medal, in the field of Physics, this study demonstrates that the SDC and D h-index are superior to all benchmark metrics, including the conventional and normalized disruption-based measures, in terms of convergent validity. Second, this study analyzes the distribution of academic characteristics between award-winning and non-laureates, explores various metrics of scientists with high SDC and Scientists' Consolidating Citation (SCC), and finds that disruptive impact can identify successful scientists from their counterparts and serve as an early signal of successful scientists. Third, this study reveals that the disruptive citation proposed in this study is less susceptible to manipulation, making it a more reliable metric for assessing a scientist's or a single paper's disruptive impact than the CD-index. The results suggest that the SDC and D h-index are reliable metrics for measuring scientists' innovative influence and can aid in the development of future scientific research. Overall, this study provides a scientifically sound and effective new perspective on measuring scientists using a dual measurement of disruptive and consolidating influence.

1. Introduction

Scientific progress can be viewed as a dynamic and evolving system (Winnink, Tijssen, & van Raan, 2019). Most scientists builds their researches upon previous findings of others (Fortunato et al., 2018), a concept known as "standing on the shoulders of giants" (Jo, Liu, & Wang, 2022), which forms the inheritance and flow network of scientific knowledge (Ghosal, Tiwary, Patton, & Stahl, 2022).

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https://doi.org/10.1016/j.ipm.2023.103420
Received 26 February 2023; Received in revised form 19 April 2023; Accepted 30 May 2023
Available online 20 June 2023
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However, disruptive studies have the ability to break existing research paradigms within the network of scientific knowledge (Kuhn, 1962; Popper, 1934), opening up new knowledge areas. In recent years, a pool of researches has analyzed the distribution and trends of research with disruptive impact in the scientific field, based on large patent or literature network data (Park, Leahey, & Funk, 2023; Uzzi, Mukherjee, Stringer, & Jones, 2013; Wu, Wang, & Evans, 2019). The concept of disruptive impact corresponds to consolidation (Park et al., 2023), wherein disruptive impact reflects the destructive innovation of existing paradigms, while consolidation reflects the inheritance and continuation of traditional fields. The study of disruptive and consolidating impact has become an important issue in the fields of science of science (Park et al., 2023; Wang & Barabási, 2021; Wu et al., 2019) as well as information science (Leydesdorff & Bornmann, 2021; Ruan, Lyu, Gong, Cheng, & Li, 2021; Wang et al., 2022; Wei, Li, & Shi, 2023).

By taking into consideration deep information on the flow of scientific knowledge, disruptive and consolidating impacts can be quantitatively observed in citation networks. The formal expression of these impacts can be traced back to the disruptive index (CD-index) proposed by Funk and Owen-Smith (2017) in patent documents, which measures whether patents consolidate or disrupt existing technological trends. Wu et al. (2019) and Park et al. (2023) have extended this concept to the field of scientific literature in the bibliometric network. The CD-index measures the consolidating and disruptive impact of scientific research by assessing the deep-level citation network structure of papers (Azoulay, 2019). The concept of disruptive and consolidating impact has been widely applied and empirically tested in various aspects, such as the permeation and flow of knowledge entities (Wang et al., 2022), the evolution of the disruptiveness in researches (Park et al., 2023), and the characteristics of Nobel Prize papers (Wei et al., 2023). This concept provides new perspectives and dimensions for measuring scientific impact.

Disruptive or consolidating impact can also be applied in the evaluation of individual scientists. Evaluating scientists is a crucial issue in various contexts, such as grant applications, performance evaluation, personnel promotion and reward mechanisms (Wang, Zhou, & Zeng, 2023), which rely heavily on accurate and comprehensive measures of scientists' impact (Fortunato et al., 2018; Foster, Rzhetsky, & Evans, 2015; Yin, Wang, Evans, & Wang, 2019). However, traditional scholarly metrics suffer from limitations in measuring the innovation level of scientists and lack convergent validity (Petersen, Riccaboni, Stanley, & Pammolli, 2012), while peer review systems also face challenges in coping with the increasing volume of scientific publications (Wang & Barabási, 2021). As a result, the scientific community is experiencing the disruption stagnation (Park et al., 2023), where novel and innovative ideas struggle to gain recognition and influence.

2. Research objective

In this study, we aim to address the following research questions:

(1) What are the more rational metrics for evaluating scientists from the perspective of disruption and consolidation, and how can we distinguish between disruptive and consolidating scientists?
(2) How do laureates and non-laureates in Physics differ in terms of their disruptive and consolidating impact?
(3) What are the patterns of dual impact and dual careers of laureates?
(4) Can the disruptive citation and CD-index be subject to manipulation by researchers through the deliberate reduction of reference count?

By answering the above research questions, this study aims to contribute to the following aspects:

(1) We introduce a set of metrics for evaluating the impact of scientists, including the Scientists' Disruptive Citation (SDC), Scientists' Consolidating Citation (SCC), Disruptive h-index (D h-index), and Consolidating h-index (C h-index). Our dual measurement framework distinguishes between disruptive and consolidating scientists, characterizing their impact from a dual perspective. These approaches enhance the rationality of evaluating scientists' innovative level and potential, providing new methods and perspectives for academic evaluation and performance assessment.
(2) We propose a condensed classification of scientists into two academic characteristics, disruptive and consolidating scientists, based on the concept of disruptive impact. By analyzing the distribution of academic characteristics between award-winning and non-laureates in the field of physics and exploring various metrics of scientists with high SDC and high SCC, our study provides a scientifically sound and effective new perspective on measuring scientists.
(3) We provide empirical evidence that the SDC and D h-index are highly consistent with traditional metrics and outperform benchmark metrics such as total citation and h-index in terms of convergence validity. The SDC and D h-index are reliable metrics for measuring scientists' innovative influence and aid in measuring their academic standing. We also provide evidence for identifying potential prominent scientists in their early careers using SDC.
(4) We investigate the susceptibility of disruption-based metrics to manipulation and reveal that the disruptive citation proposed in this study is less susceptible to manipulation than the CD-index. Furthermore, our paper-level analysis indicates that deliberately reducing the number of references cited in a paper may actually decrease disruptive citation. Our study provides important insights into the susceptibility of disruption-based metrics to manipulation.

The remainder of this paper is organized as follows. In Section 3, we provide a review of the current state of scientist evaluation, as well as disruption and consolidation in the field. In Section 4, we introduce our novel metrics and measurement framework. In Section 5, we elaborate on the dataset and preprocessing procedures used in this study. In Section 6, we conduct a comprehensive empirical study and present a thorough analysis of the results. In Section 7, we perform further analysis and check the robustness of our findings.

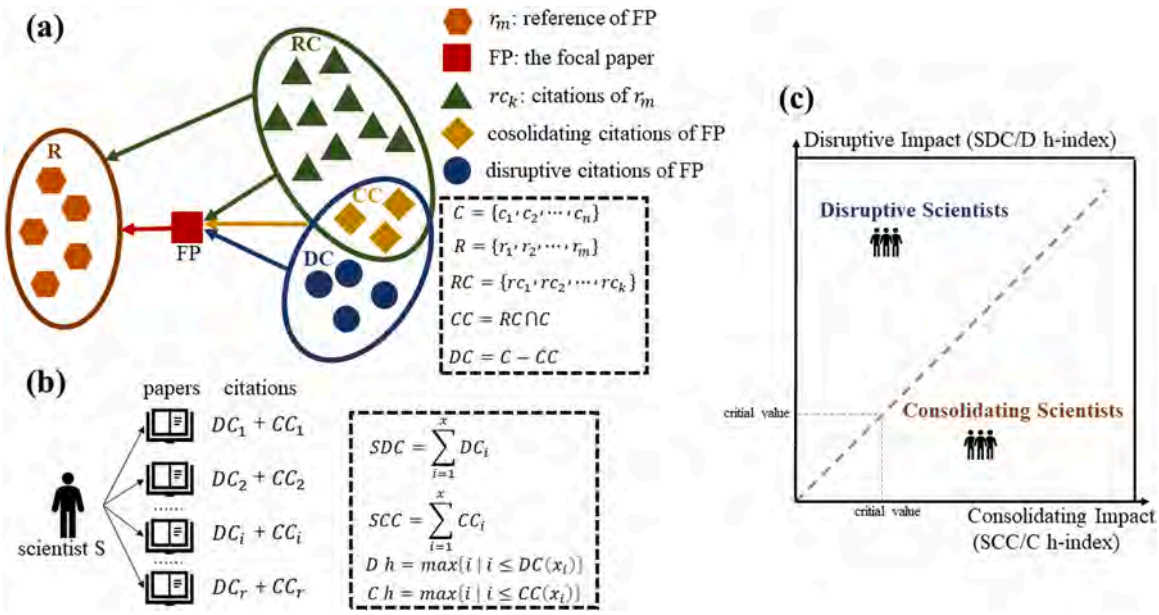


Fig. 1. Metric basis and dual academic characteristics of disruptive and consolidating influence of scientists. (a) Disruptive citation (DC) and Consolidating citation (CC) of the focal paper. (b) The Scientists' Disruptive Citation (SDC), Scientists' Consolidating Citation (SCC), Disruptive h-index and Consolidating h-index of a scientist. (c) The dual academic characteristic framework, where disruptive scientists are above the line and consolidating scientists are below the line. The critical values can be assigned as the quantiles of SDC and SCC.

In Section 8, we discuss the implications and suggest directions for future research.

3. Literature review

3.1. Scientist evaluation

Traditional metrics for measuring scientists' impact, such as publication count, citation, and the h-index (Hirsch, 2005), are widely used due to their simplicity and ease of calculation (Roldan-Valadez, Yoselin Salazar-Ruiz, Ibarra-Contreras, & Rios, 2019). However, these metrics have limitations as they provide only a single-dimensional view of a scientist's impact (Zhang, Wang, Zipperle, Abbasi, & Tani, 2023), making it difficult to measure the deeper value and intrinsic meaning of their work (Waltman & Van Eck, 2012). From the perspective of citation networks, traditional metrics consider only local information, ignoring higher-order information that could help in measuring the disruptive or consolidating impact of scientific research (Zeng et al., 2017). Furthermore, studies have shown that citation-based metrics lack convergence and effectiveness in measuring milestone research and top scientists' impact (Bornmann & Tekles, 2021; Herrmannova, Patton, Knoth, & Stahl, 2018; Wang et al., 2023). This has led scientists to resist traditional metrics through the *San Francisco Declaration* (Cagan, 2013) and the *Leiden Manifesto* (Hicks, Wouters, Waltman, de Rijcke, & Rafols, 2015), and to call for more comprehensive metrics.

In the current evaluation system, disruptive researches that do not conform to the existing paradigm are often difficult to publish, from the scientist's perspective (Rosenthal, 1979). Jia, Wang, and Szymanski (2017) argue that consolidating researches are more suitable for the current scientist evaluation system, as they are usually based on recognized achievements within the existing paradigm, have a greater probability of being published, and often achieve a certain amount of citation in the short term. Disruptive researches, on the other hand, tend to have greater impact in the long run, but their high difficulty, super-high time cost, sunk cost, and the risk of failure and rejection have deterred many scientists from pursuing them (Wang & Uzzi, 2022; Yin et al., 2019). While focusing on conventional fields may be efficient and labor-saving for individuals (Rzhetsky, Foster, Foster, & Evans, 2015), such behavior can hinder the creative development of the overall scientific field and research paradigms from a macro perspective. Existing evaluation metrics fail to accurately characterize scientists' innovative contributions, and this, coupled with the high risk and difficulty of pursuing disruptive research, has caused more and more scientists to focus on conventional research. However, this trend ultimately hinders the creative development of the overall scientific field and research paradigms, and may lead to scientific stagnation in disruption (Park et al., 2023).

3.2. Disruption and consolidation

The notion of disruptive innovation was first introduced in Bower's *Disruptive Technologies: Catching the Wave* (Bower, 1995). In the context of scientific research, the knowledge basis and impact of papers and patents can be categorized as either disruptive or

consolidating. Citation links in the knowledge network often serve as a manifestation of the forward and backward impact of papers and patents. Funk and Owen-Smith (2017) proposed the Consolidation-Disruption (CD) index to evaluate the disruption or consolidation of patents to existing technological trends. The CD-index measures the use of existing research results by new researchers. Wu et al. (2019) and (Park et al., 2023) extended this approach to the field of scientific literature. The CD-index quantitatively measures the consolidation and disruptive influence of scientific research by examining the deep citation network structure of papers (Yang et al., 2023). Azoulay (2019) provided an intuitive explanation for the CD-index: for a core article FP, if many papers citing FP also cite most of the references cited by FP, then FP is considered to consolidate its disciplinary paradigm. In contrast, if the future citation of FP does not acknowledge the references cited by FP, it can be considered to disrupt the research paradigm of its disciplinary field and even create new fields.

Leydesdorff and Bornmann (2021) and Chen, Shao, and Fan (2021) categorized the impact of scientific research into two dimensions: disruptive impact and consolidating impact based on the CD index. Bu, Waltman, and Huang (2021) further explored the evaluation framework of papers based on disruptive and consolidating aspects. Recently, the concept of disruptive and consolidating impact has been applied to various fields and levels, such as the penetration and flow of disruptive knowledge entities (Wang et al., 2022), the evolution pattern of disruptive research results (Park et al., 2023), and the distribution of consolidating and disruptive impact in Nobel Prize papers (Wei et al., 2023), among others. However, the concept of disruptive and consolidating impact has not yet been applied to the evaluation of scientists. This study aims to fill this gap.

4. Metrics and framework

4.1. New metrics

Building upon the work of scientists Funk and Owen Smith (2017), Wu et al. (2019), and Leydesdorff and Bornmann (2021), this paper proposes a new approach to measuring the impact of scholarly research by dividing the impact of a single article into two categories: Disruptive Citation (DC) and Consolidating Citation (CC). As illustrated in Fig. 1a, a focal paper (FP) in the citation network is considered, along with its reference set $R = \{r_1, r_2, \cdots, r_m\}$ and citation set $C = \{c_1, c_2, \cdots, c_n\}$. Together, R, FP, and C form a coherent knowledge flow sub-network, providing deep citation information about the forward and backward central nodes in the citation network. To explore the implicit relationships among articles, the citation set of R is also considered, denoted as $RC = \{rc_1, rc_2, \cdots, rc_k\}$. It should be noted that, unlike R and C, the nodes in RC often include more nodes because they point to multiple articles. Therefore, the consolidating citation of FP can be represented as $CC = RC \cap C$, and the disruptive citation can be represented as $DC = C - CC$.

As illustrated in Fig. 1b, we further propose a set of metrics for gaging scientists' impact based on their disruptive and consolidating citation. Starting with all the papers published by a scientist, they are categorized based on their citation set. The total citation of a scientist can then be divided into two categories: the scientist's disruptive citation (SDC) and the scientist's consolidating citation (SCC), forming a dual oppositional relationship, where the sum of SDC and SCC equals the total citation. For instance, suppose scientist A has published x papers within a certain time window; their SDC and SCC are defined as:

$$SDC = \sum_{i=1}^{x} DC_i \tag{1}$$

$$SCC = \sum_{i=1}^{x} CC_i \tag{2}$$

To measure the dual impact of scientists, both the disruptive citation and consolidating citation are used. However, the citation count is only one dimension of influence. Another important dimension is the publication numbers. To incorporate this dimension, the disruptive h-index and consolidating h-index are proposed.

Let $X = \{x_1, x_2, \cdots, x_r\}$ be the set of all papers published by a scientist S, sorted in descending order according to their disruptive citation (DC) and consolidating citation (CC), respectively. Then, the set of papers with the highest DC values is denoted as X_{SDC}, and the set of papers with the highest CC values is denoted as X_{SCC}:

$$X_{SDC} = \{x_1, x_2, \cdots, x_r \mid DC(x_1) \rangle DC(x_2) > \cdots > DC(x_r)\} \tag{3}$$

$$X_{SCC} = \{x_1, x_2, \cdots, x_r \mid CC(x_1) \rangle CC(x_2) > \cdots > CC(x_r)\} \tag{4}$$

Building on the original definition of the h-index by Hirsch (2005), which states that a scientist has an h-index if he/she has h papers with at least h citation, the disruptive h-index and consolidating h-index are defined as follows:

Definition 1. Disruptive h-index (D h) represents the maximum number of papers in the set X_{SDC} published by scientist S that has disruptive citation greater than or equal to D h.

$$D\ h = max\{i \mid i \leq DC(x_i)\} \tag{5}$$

Definition 2. Consolidating h-index (C h) represents the maximum number of papers in the set X_{SCC} published by scientist S that has consolidating citation greater than or equal to C h.

$$C\ h = max\{i \mid i \leq CC(x_i)\} \tag{6}$$

Table 1
A paper-level description of the APS dataset.

	Disruptive Citation	Consolidating Citation	Citation	References	CD-index
Sample Size	463,348	463,348	463,348	463,348	463,348
Mean	3.72	6.52	10.24	10.24	0.023
Std	18.55	16.60	29.83	9.67	0.178
Min	0	0	0	0	−1
Median	1	3	4	8	−0.01
Max	4089	3992	5464	583	1
Skewness	56.02	52.91	41.82	7.41	4.52
Kurtosis	7541.45	9126.34	4664.55	218.09	22.26

As illustrated in Fig. 1c, using these metrics, a dual-dimension measurement framework of disruptive and consolidating impact is constructed. This framework condenses different types of scientists with distinct impact into two academic features: (1) Disruptive scientists exhibit high disruptive impact, often being innovative and pursuing breakthroughs. (2) Consolidating scientists exhibit high consolidating impact.

4.2. Benchmarks

To evaluate the effectiveness and reliability of our proposed metrics, we employ various benchmark metrics to evaluate the impact of scientists. First, we use conventional measures that have been widely used in previous studies to gage the impact of scientists (Way, Morgan, Larremore, & Clauset, 2019). These measures include the number of publications, the total citation, the h-index (Hirsch, 2005), and the g-index (Egghe, 2006), which serve as our conventional benchmarks.

Second, to address the concerns regarding the normalization of the disruption-based metrics (Wu et al., 2019), we propose three additional benchmark measures that evaluate the impact of scientists from the perspective of disruption and consolidation. These measures are the Total CD-index, Total D-index, and Total C-index, and they are calculated as the sum of the CD-index, D-index, and C-index values (Leydesdorff, Tekles, & Bornmann, 2021) of each paper authored by the scientist. The Total CD-index, Total D-index, and Total C-index are designed to capture a scientist's disruptive and consolidating impact, respectively. The formulas for these metrics are provided as follows, where $X = \{x_1, x_2, \cdots, x_r\}$ represents the set of all papers published by a scientist S:

$$total\ CD\ index\ =\ \sum \frac{DC(x_i) - CC(x_i)}{DC(x_i) + CC(x_i) + RC(x_i)} \tag{7}$$

$$total\ D\ index\ =\ \sum \frac{DC(x_i)}{DC(x_i) + CC(x_i) + RC(x_i)} \tag{8}$$

$$total\ C\ index\ =\ \sum \frac{CC(x_i)}{DC(x_i) + CC(x_i) + RC(x_i)} \tag{9}$$

We present a third benchmark measure in order to compare our proposed metric with existing ones that consider both the citation and the disruption, as discussed in previous studies (Wei et al., 2023), . To construct this measure, we use the sum of the citation percentile and the disruption percentile, denoted as Citation-CD P. The citation percentile and CD-index percentile of each paper are represented by $\mathrm{CitP}(x_i)$ and $\mathrm{CDP}(x_i)$, respectively. The formula for this benchmark measure is shown as follows:

$$Citation - CD\ P = \sum (CitP(x_i)\ +\ CDP(x_i)) \tag{10}$$

This measure integrates the percentile ranks of both the CD-index and the total citation to capture both the disruption and the citation. By comparing our proposed metric with these benchmark measures, we can assess the strengths and weaknesses of our approach and gain a more comprehensive understanding of the impact of scientists.

5. Data and preprocessing

5.1. Citation network data

This study is based on citation data provided by the American Physical Society (APS), which encompasses 19 journals, including the Physical Review series, and covers all literature and citation data from 1893 to 2021. The dataset comprises a total of 700,035 research papers and 9370,286 citation links. In this study, we focused on publications published before 2010 and extracted a subset of the APS dataset, which consists of 463,348 papers. By limiting the scope to a specific time period, we aimed to avoid potential confounding factors caused by changes in the citation behavior or publication patterns over time (Zeng et al., 2017). We constructed a large citation network using Python-igraph-0.10.2 and Python-networkx-2.8.8, and established a large adjacency matrix for analysis. In the network, indegree represents the number of citations, while outdegree represents the number of references. We calculated relevant metrics using programs such as Python-scipy-1.10.1, and performed consistency checks and convergent validity analyses to ensure the validity of the

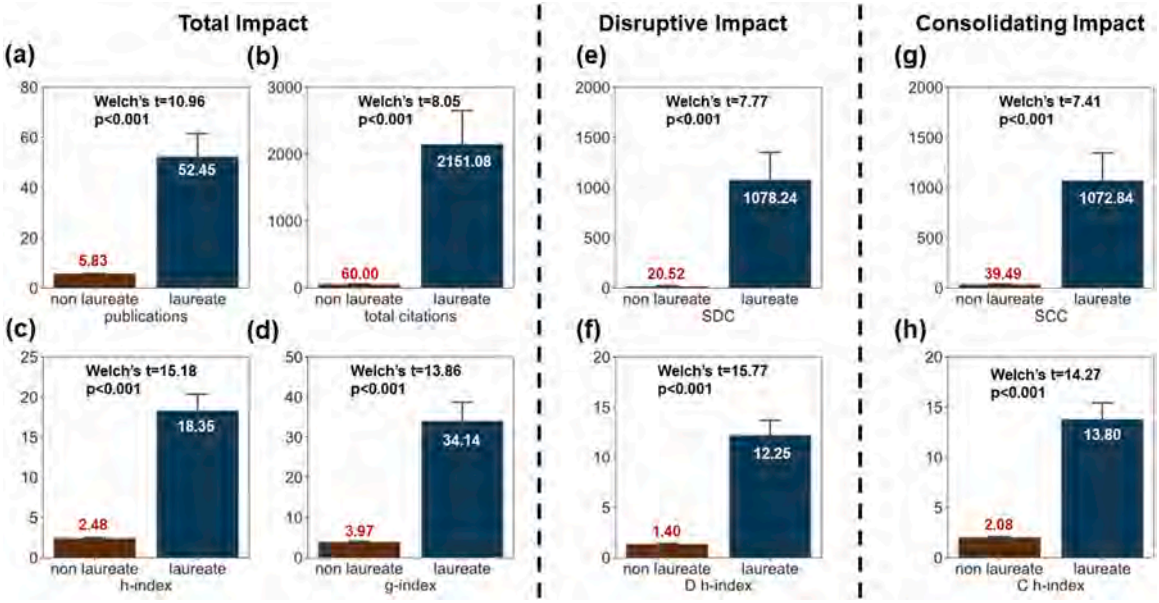


Fig. 2. Laureates have a significant advantage over non-laureates across different metrics. The values for Welch's *t*-test are as follows: (a) 10.96 for publication numbers, (b) 8.05 for total citation, (c) 15.18 for h-index, (d) 13.86 for g-index, (e) 7.77 for SDC, (f) 15.77 for D h-index, (g) 7.41 for SCC, and (h) 14.27 for C h-index.

results.

Table 1 presents paper-level descriptive statistics for the APS dataset, which reveals highly skewed distributions of Disruptive Citation (DC) and Consolidating Citation (CC). On average, DC is about half of CC. Appendix Fig. B1 shows their distributions across years and journals, indicating that DC is unevenly distributed across both.

5.2. Name disambiguation

Disambiguation is a crucial and challenging step in the process of quantitatively measuring and evaluating scientists (Wang, Song, & Barabási, 2013; Yin et al., 2019; Zeng et al., 2017), particularly when dealing with large datasets such as the APS, where the same author may appear under different names, or different authors may have the same name. To address this, we followed the approach of Sinatra, Wang, Deville, Song, and Barabási (2016) to perform author disambiguation. Specifically, we extracted all name pairs (i.e., any two author names) from the APS dataset, and used regular expressions to match them, retaining only pairs that satisfied the following criteria: (1) the surnames of the two authors are the same, (2) the abbreviations and middle names of the names are the same, and (3) the two authors cite each other at least once or have similar institutional affiliations. To further disambiguate scientists with nebulous names, we used the Physics Tree dataset for comparison. In the end, we identified 234,086 distinct scientists, which is a smaller number compared to the 236,884 distinct authors identified in Sinatra et al. (2016).

Notably, in this study, we did not use any fraction credit allocation method. Instead, we assigned equal credit to all authors of all publications, following the full credit counting method (Waltman, 2016).

5.3. Laureate dataset

To assess the effectiveness of the metrics in identifying outstanding physics scientists, we collected data on winners of several prestigious international awards, including the Nobel Prize, the Wolf Prize and the Dirac Medal. The Nobel Prize and the Wolf Prize are both recognized as the top honors in science, reflecting the highest level of innovation and real contributions in the discipline. The Dirac Medal, on the other hand, is specifically awarded to academic giants who have not been awarded the above two awards. In the field of physics, the scientists who have won these honors have made the most outstanding contributions to the discipline (Way et al., 2019).

The disambiguated author names in APS were matched with these laureates by using various sources, including their homepages, Wikipedia, and Physics Tree biographical information. To ensure a high level of scholarly activity, only authors who published at least 5 papers in the APS dataset were considered. In total, we identified 130 physics scientists who had won these awards.

We compared various metrics, including the number of publications, total citation, h-index, g-index, Scientists' Disruptive Citation (SDC), Scientists' Consolidating Citation (SCC), Disruptive h-index (D h), and Consolidating h-index (C h), between the award winners and other scientists in the APS dataset (Fig. 2, Appendix Table A1). The differences in the metrics were evaluated using the two-tailed Welch's *t*-test. As shown in Fig. 2, the metrics of the award winners were significantly higher than those of non-award winners (Welch's

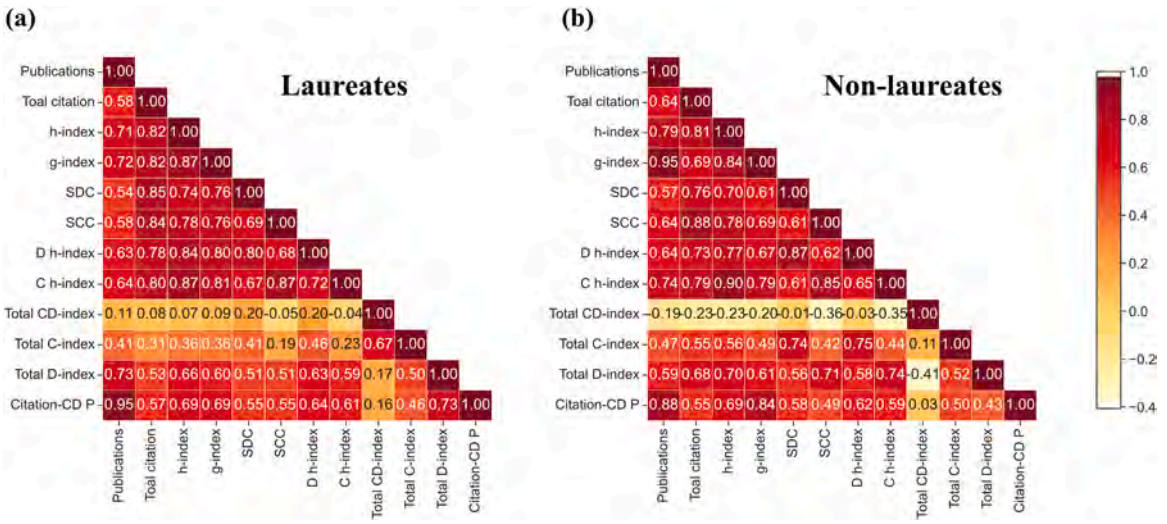


Fig. 3. Kendall's tau correlation coefficients for laureates and non-laureates in disruptive metrics, consolidating metrics and benchmark metrics. The correlation coefficients in publication numbers, h-index, g-index, total citation, SDC, SCC, D h-index, C h-index and other benchmarks for (a) laureates and (b) non-laureates.

$t>7$, $p<0.001$), indicating that the metrics are effective in identifying outstanding scientists. We further analyzed the consistency and convergent validity of the metrics.

Regarding the metric distribution, the sample size of the award winners was much smaller than that of non-award winners, and the mean and standard deviation of various metrics were larger. Even at the 75th percentile, the various metrics of non-award winners were still relatively low, which could be attributed to the preferential attachment effect (Nacher, Hayashida, & Akutsu, 2009) and the Matthew effect (Wolcott et al., 2016), leading to a power law distribution.

6. Analysis and results

6.1. Consistency analysis

This study used Kendall's Tau coefficient (Lü, Zhou, Zhang, & Stanley, 2016) to measure the degree of consistency between the new metrics proposed in this paper and the traditional benchmark metrics, including total citation, total publication count, and h-index. Kendall's Tau is a measure of the correlation between two sets of rankings or sequences, with values ranging from −1 (total disagreement) to +1 (total agreement). The formula is given by:

$$\tau = \frac{n^c - n^d}{\sqrt{(n^c + n^d + n^x) \times (n^c + n^d + n^y)}} \tag{11}$$

where n^c and n^d represent the number of sample observations with consistent and inconsistent rankings, respectively, and n^x and n^y represent the number of observations with the same rankings.

Fig. 3 shows the results of the consistency analysis for both award-winning and non-laureates. The new metrics, including SDC, SCC, D h-index, and C h-index, are highly correlated with the traditional metrics for both groups (Fig. 3a and 3b), indicating the consistency of the new metrics with existing measures.

Interestingly, the disruptive impact (SDC) and consolidating impact (SCC) are highly correlated, as indicated by the high correlation coefficients between SDC and SCC (0.69 and 0.61 for laureates and non-laureates, respectively) and between D h-index and C h-index (0.72 and 0.65 for laureates and non-laureates, respectively). This finding may reflect the Matthew effect in the academic field (Wolcott et al., 2016), where scientists' high disruptive achievements contribute to their academic reputation (Petersen et al., 2014), enabling their consolidating research to also have higher impact. The mutually reinforcing effect mechanism for dual impact is further supported by this paper in the following sections.

6.2. Convergent validity (IR)

To confirm the validity and effectiveness of the new measurement metrics, we conducted a convergent validity analysis with benchmark metrics. The convergent validity of an metric measures the extent to which it effectively captures the scope and efficiency of its target object (Bornmann, Devarakonda, Tekles, & Chacko, 2020a). First, we evaluated the convergent validity of the metrics using the identification rate (IR). The IR represents the proportion of laureates among the top z fraction of scientists ranked by a specific metric. A higher IR value indicates stronger convergent validity of the metric. We calculated the IR of the metric by considering

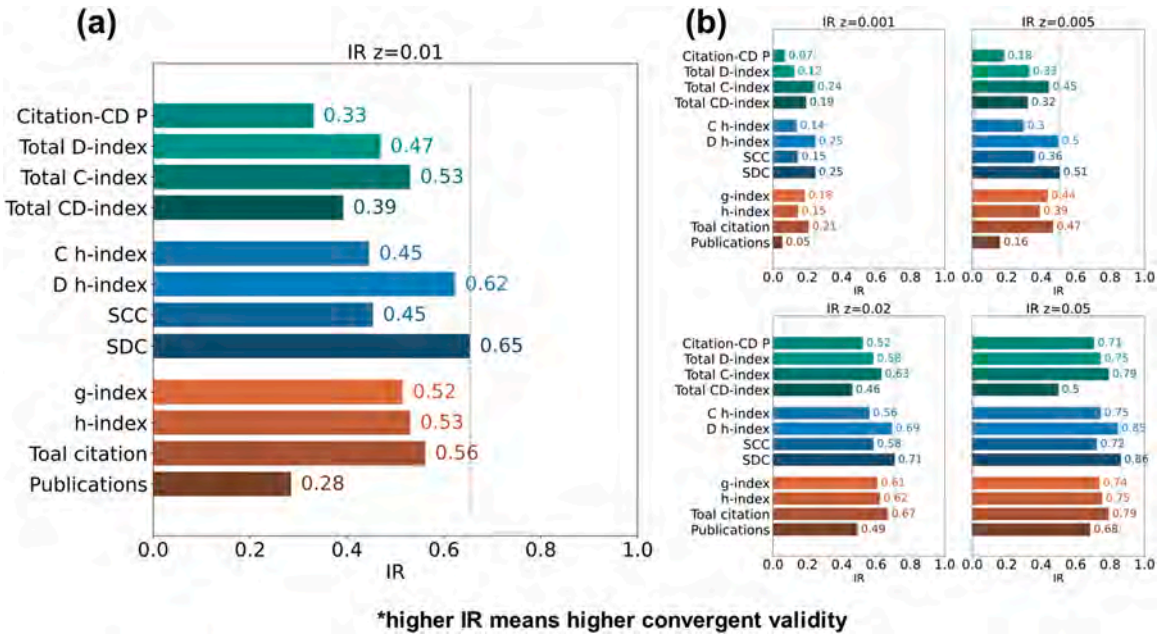


Fig. 4. Convergent validity: the identification rate (IR) of laureates for disruptive metrics, consolidating metrics and benchmark metrics. (a) The identification rate results with $z = 0.01$ (1%) as the convergent validity of publication numbers, total citation, h-index, g-index, SDC, SCC, D h-index C h-index and other benchmarks. We use the set of orange colors to denote the traditional measures, the set of blue colors to denote the proposed metrics, and the set of green colors to denote the normalized disruption-based metrics. (b) Other z values for robustness check, including $z = 0.001$ (0.1%), $z = 0.005$ (0.5%), $z = 0.02$ (2%) and $z = 0.05$ (5%). Note that higher IR means higher convergent validity.

the top 1% ranked scientists as the measurement area and verified the robustness of the metric at different thresholds, following the approach of Xu, Mariani, Lu, and Medo (2020).

As shown in Fig. 4a, the Scientists' Disruptive Citation (SDC) metric showed the best performance in identifying laureates among all metrics. Furthermore, the Disruptive h-index (D h-index) also outperformed consolidating impact metrics, traditional measures, and normalized disruption-based measures in identifying laureates. These findings highlight the superior performance of the SDC and D h-index in measuring scientists' innovative influence.

To verify the robustness of the results, z-values were set to 0.001, 0.005, 0.02, and 0.05, as shown in Fig. 4b. The results of the robustness tests show that the convergent validity of SDC and D h-index is markedly superior to consolidation impact metrics and benchmark metrics. Additionally, SDC and D h-index have a significant advantage over other metrics in identifying laureates. However, as the threshold (z) increases, this identification advantage gradually decreases, but still remains superior to benchmark metrics.

It is worth highlighting that the identification rate (IR) of publications is considerably low when used to identify top scientists (Fig. 4b, $z = 0.001$ and $z = 0.005$), indicating that this metric is inadequate to reflect scientists' true impact and innovation ability. Our consistency analysis reveals that there is a weak correlation between publication counts and disruptive impact metrics (as discussed in Section 6.1). Therefore, relying on publication counts as a measure of scientists' innovation level is not recommended. Furthermore, the combination of the CD-index and citation, known as the Citation-CD P metric (Wei et al., 2023), also performs poorly in identifying top scientists. This implies that a simple combination of the CD-index and citation is not a reliable method to evaluate scientists. We also note that the normalized disruption-based metrics, including the Total CD-index, Total C-index, and Total D-index, proposed to address concerns regarding normalization for disruption-based metrics, did not perform well in identifying laureates compared to SDC and D h metrics. One possible reason for this is that the normalization may have had an adverse effect on the metrics' ability to distinguish between high-impact papers and papers with high disruptive impact. Normalization reduces the effect of the impact of the papers, which may have a greater effect on laureate selection. Additionally, these metrics do not fully capture the nuanced differences between different types of disruptive impact.

6.3. Convergent validity (AR)

To further validate the effectiveness of our new metrics, we use the average ranking (AR) of all laureates to assess their convergent validity. Unlike IR, which focuses on recall rate (Lü et al., 2012), AR measures the average ranking of all laureates under a specific metric. Considering a metric m and the laureate set $\{v_1, v_2, \cdots\}$, the difference between the ranking of the lowest-ranked laureate and the highest-ranked laureate was taken as the denominator to obtain the average ranking (AR). A lower AR value indicates stronger convergent validity of the metric.

Average ranking of the laureates can quantitatively reflect the convergent validity of the quantitative metrics (Wang, Xu, Mariani,

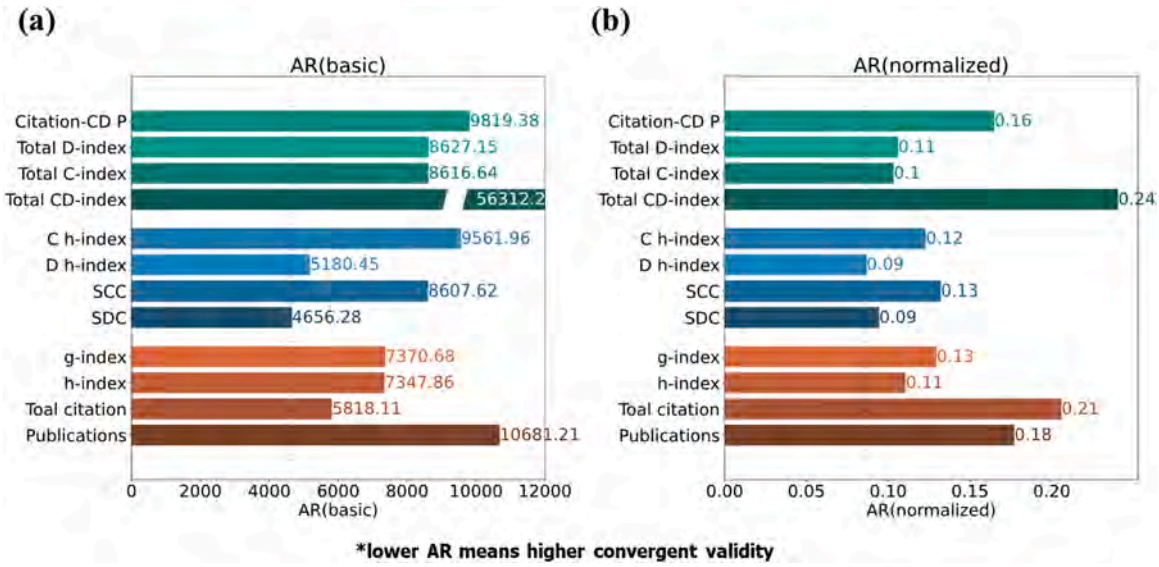


Fig. 5. Convergent validity: the average ranking (AR) of laureates for disruptive metrics, consolidating metrics and benchmark metrics. (a) The basic average ranking results as the convergent validity of publication numbers, total citation, h-index, g-index, SDC, SCC, D h-index C h-index and other benchmarks. We use the set of orange colors to denote the traditional measures, the set of blue colors to denote the proposed metrics, and the set of green colors to denote the normalized disruption-based metrics. (b) The normalized average ranking for robustness check. Note that lower AR represents higher convergent validity.

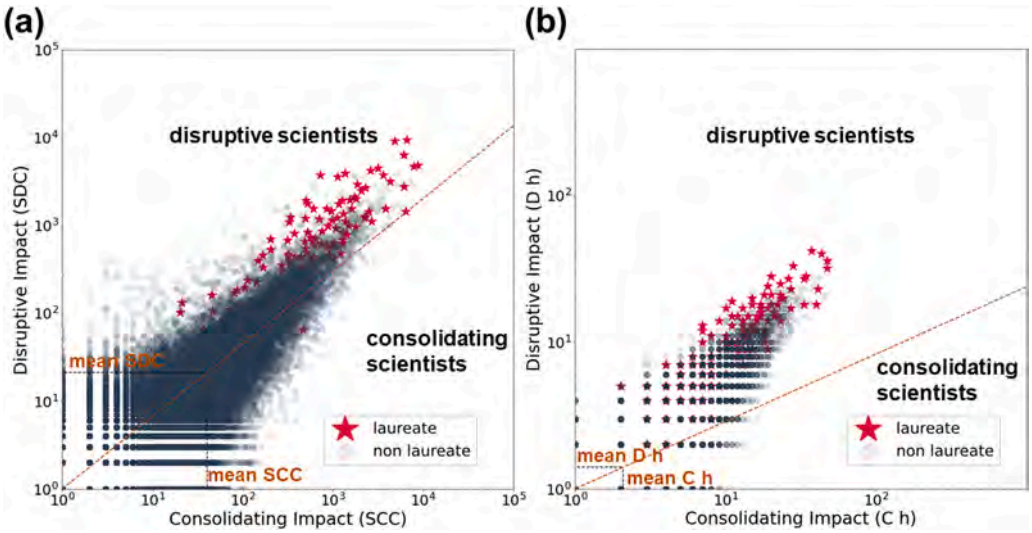


Fig. 6. Dual impact measures as well as dual academic characteristics, i.e., disruptive scientists and consolidating scientists. The red pentagram represents the laureates, and the blue circle refers to the non-laureates; the blue dashed line represents the mean value, and the green dashed line means the dividing line. The data on both the horizontal and vertical axes are commonly processed using logarithms (log10). (a) Disruptive scientists and consolidating scientists based on SDC and SCC. (b) Disruptive scientists and consolidating scientists based on D h-index and C h-index.

& Lü, 2021, 2023). The results for purposed metrics and benchmarks are shown in Fig. 5a. The AR results indicate that both SDC and D h-index have excellent convergent validity, and are significantly better than the benchmark metrics. In contrast, the convergent validity of SCC and C h-index is weaker than the benchmark metrics such as h-index and g-index.

To address the potential influence of outliers or extreme values on average rankings, we standardized the rankings of individual scientists under different metrics using the approach of Mariani, Medo, and Zhang (2016). This standardized average ranking was calculated by taking the difference between the ranking of the lowest-ranked laureate and the highest-ranked laureate and dividing it by the denominator, which was the difference between the maximum and minimum ranking of all laureates. The formula of normalized AR was $\widetilde{R}(m,v_i) = \frac{R(m,v_i)}{\max(R(m,v))-min(R(m,v))}$. Fig. 5b presents the normalized AR results, which show that SDC and D h-index

Table 2
The top scientists with the highest disruptive impact and consolidating impact, respectively.

Top 5 scientists with the highest disruptive impact (SDC)								
Scientists	Pub.	h	T. Cit.	SDC	SCC	D h	C h	Prize
Walter Kohn	115	36	15,906	9361	6545	27	26	Nobel
Philip W. Anderson	138	55	13,920	9091	4829	42	37	Nobel
Steven Weinberg	133	58	12,435	6286	6149	40	43	Dirac
Patrick A. Lee	203	57	13,564	4820	8744	36	47	Dirac
Bertrand I. Halperin	185	56	12,470	4646	7824	32	47	Wolf
Top 5 scientists with the highest consolidating impact (SCC)								
Scientists	Pub.	h	T. Cit.	SDC	SCC	D h	C h	Prize
Patrick A. Lee	203	57	13,564	4820	8744	36	47	Dirac
Bertrand I. Halperin	185	56	12,470	4646	7824	32	47	Wolf
L. J. Sham	137	39	10,246	2838	7408	21	31	none
Gen Shirane	385	53	10,494	3248	7246	27	41	none
Sankar Das Sarma	442	42	8285	1668	6617	18	36	none

perform the best, while total CD-index performs the worst in the normalized AR. As metrics for measuring disruptive influence, SDC and D h-index each have distinct advantages in different evaluation tasks. Specifically, SDC shows a higher AR, while D h-index exhibits a higher normalized AR.

Overall, our convergent validity analysis demonstrates that the newly proposed metrics, including SDC and D h-index, show superior performance in identifying and ranking outstanding physics scientists, providing a more comprehensive and accurate measure of their innovative impact compared to traditional metrics and normalized disruption-based metrics.

6.4. Dual impact

To assess the dual impact of scientists from the perspective of both disruptiveness and consolidation, we present two evaluation frameworks: one based on Scientists' Disruptive Citation (SDC) and Scientists' Consolidating Citation (SCC) metrics and another based on Disruptive h-index (D h-index) and Consolidating h-index (C h-index) metrics, as plotted in Fig. 6. The dividing line between disruptive and consolidating scientists is determined by the mean values of SDC and SCC as critical values. The result shows that laureates tend to exhibit more disruptive characteristics, while only a few consolidating scientists become prize winners. The observation is consistent with the argument that disruptive research is more likely to lead to revolutionary discoveries (Lin, Evans, & Wu, 2022; Winnink & Tijssen, 2015).

Fig. 6b shows a similar result to Fig. 6a but from the perspective of dual impact evaluation framework using D h-index and C h-index. The D h-index and C h-index represent the number of disruptive and consolidating citations required to achieve the same number of citations as the total citation for each scientist. The robustness of the dual impact evaluation framework is demonstrated in Appendix Fig. B2, where we vary the critical values from the 50th to 95th percentiles. The results consistently show a significant distinction between laureates in terms of their disruptive and consolidating impact.

The dual impact evaluation framework proposed in this study provides a comprehensive perspective for evaluating the impact of scientists. By incorporating both disruptiveness and consolidation, we can better understand the diverse career paths of scientists and the underlying mechanisms of scientific discoveries. This framework highlights the importance of disruptive research in advancing science and sheds light on the diverse career paths of scientists.

To provide further insight into the differences between disruptive impact and consolidating impact, we conducted a comparison of the top scientists with the highest SDC and SCC. Table 2 presents the top five scientists with the highest SDC and SCC, respectively. It is noteworthy that all the top five scientists with the highest SDC are laureates, while only two of the top five scientists with the highest SCC are prize-winners. These results suggest that consolidating impact metrics fail to accurately reflect the contributions of expert-selected prominent scientists. Moreover, we found that the prize-winning scientists with the highest SDC also possess high disruptive influence, indicating that disruptive impact metrics are a more effective measure of scientists' true contributions to science.

We also conducted a similar comparison of top scientists based on D h-index and C h-index, as shown in Appendix Table A2. The results indicate that disruptive impact is a more effective measure of scientists' true contributions to science, while the consolidating impact appears to play a lesser role in total citation count. Therefore, in a dual evaluation framework that considers both disruptive and consolidating influences, more emphasis should be placed on disruptive impact as it directly reflects scientists' innovation and potential.

7. Further analysis

7.1. Control group analysis

To further validate the effectiveness our proposed metrics, we conducted an additional analysis using three control groups that were selected based on their similarity in total citation, h-index, and g-index scores to those of the laureates. The goal was to compare

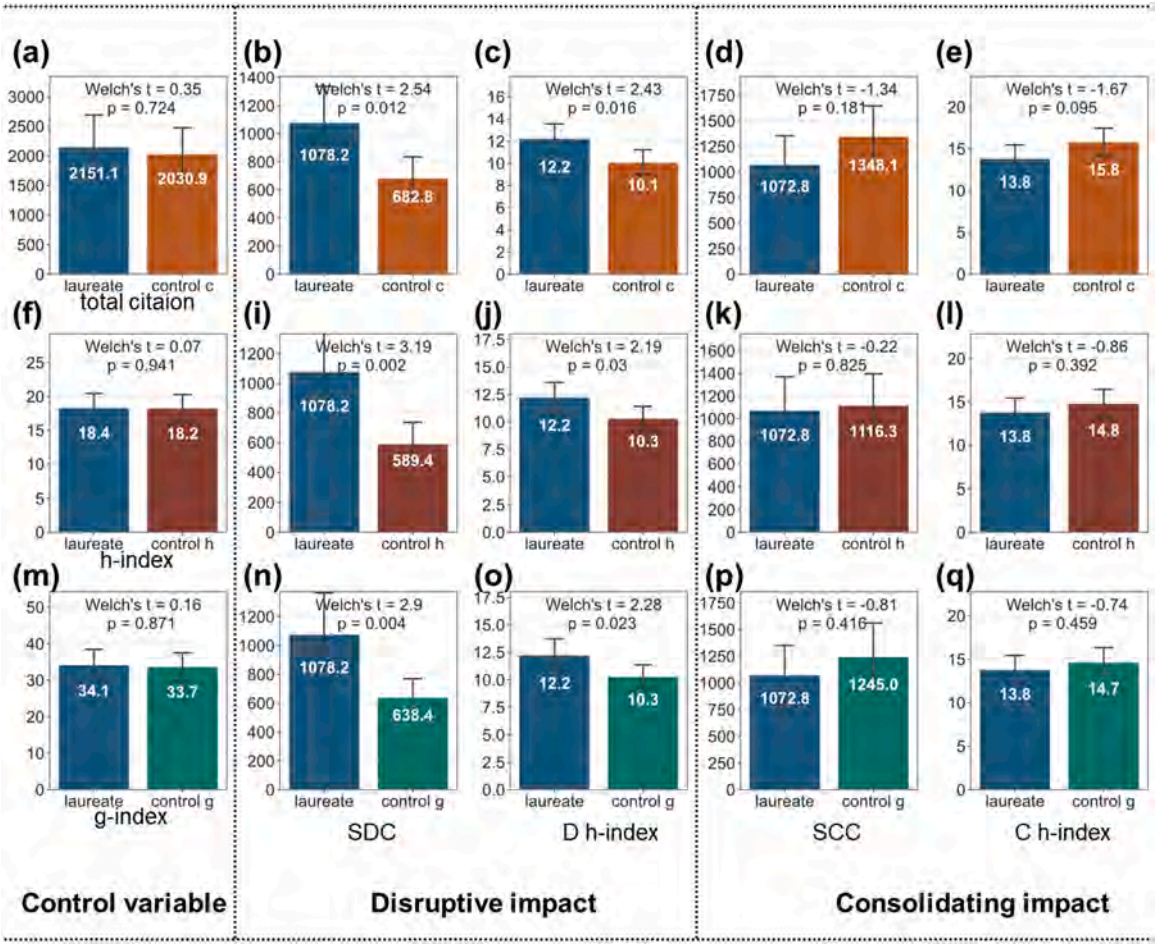


Fig. 7. Additional validations for comparing the SDC and D h-index of the laureates with those of their counterparts in three control groups, respectively. (a-e) The first control group has the similar total citation as the laureates, and the values for Welch's *t*-test are as follows: (a) 0.00 for total citation, (b) 2.54 for SDC, (c) 2.43 for D h-index, (d) −1.34 for SCC and (e) −1.67 for C h-index. (f-l) The second control group has the similar h-index as the laureates, and the values for Welch's *t*-test are as follows: (f) 0.07 for h-index, (i) 3.19 for SDC, (j) 2.19 for D h-index, (k) −0.22 for SCC and (l) −0.86 for C h-index. (m-q) The third control group has the similar g-index as the laureates, and the values for Welch's *t*-test are as follows: (m) 0.16 for g-index, (n) 2.9 for SDC, (o) 2.28 for D h-index, (p) −0.81 for SCC and (q) −74 for C h-index. The results confirm the robustness of our earlier findings and suggest that disruptive impact are useful metrics for distinguishing successful scientists from their peers, while consolidating impact might be the influence foam of the total impact of a scientist.

the disruptive impact (SDC and D h-index) and consolidating impact (SCC and C h-index) values of the laureates with those of the control groups. For each laureate, we identified another scientist in the non-laureate dataset who had the closest value in each control group.

The results of this analysis, presented in Fig. 7, show that the difference in control variables between the laureates and each control group was negligible ($p>0.7$). However, we observed a significant difference in the SDC and D h-index values of the laureates compared to those of the control groups ($p<0.05$), indicating that prominent scientists have a significantly higher disruptive influence than their counterparts.

Interestingly, the SCC and C h-index metrics did not show significant differences between laureates and their counterparts ($p>0.10$ except for Fig. 7e) in all the three control groups. In fact, the consolidating impact of the laureates was slightly lower than that of their counterparts, but the difference was not statistically significant. This implies that the consolidating impact of laureates is almost the same as that of their counterparts or that the consolidating impact may be the influence foam of the total impact of a scientist.

7.2. Dual careers

To investigate the determinants of successful scientific careers from the perspective of disruptiveness and consolidation, we calculated the SDC and SCC for each year in the careers of all laureates. For each laureate, we took the year of their first publication in APS as the starting point and calculated their SDC and SCC, as well as the proportion of each that year's SDC and SCC compared to their

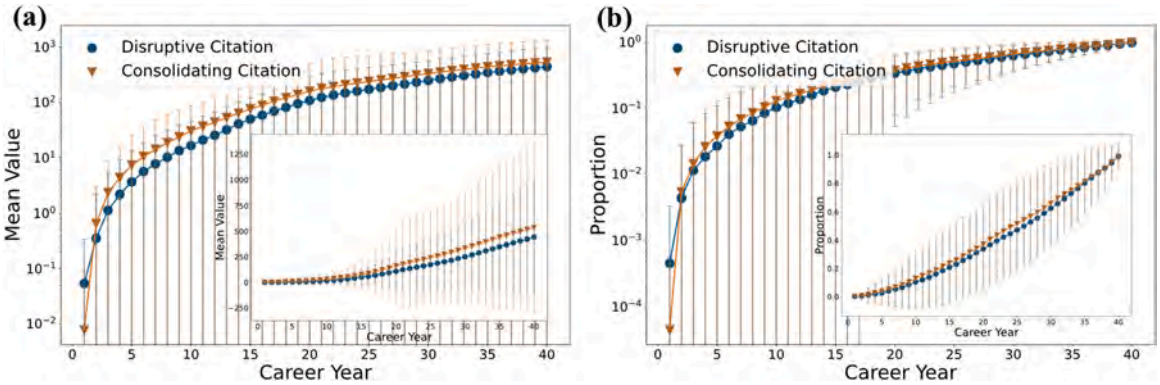


Fig. 8. Disruptive and consolidating impact careers for all laureates. (a) Mean values of disruptive impact (SDC) and consolidating impact (SCC) are presented, with the main plot showing the logarithmic value and the inset showing the non-logarithmic value. (b) The proportion of each scientist's SDC and SCC in each career year is compared to their long-term SDC and SCC. We also show the standard error bar in each career year.

Table 3
The effect of the number and impact of FP's references on the Disruptive Citation and the CD-index at the paper level.

Model	OLS							
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Disruptive citation	Disruptive citation	Disruptive citation	Disruptive citation	CD-index	CD-index	CD-index	CD-index
Independent variable								
#References	0.0846***	−0.2239***			−0.0029***	−0.003***		
	(0.003)	(0.0015)			(0.0)	(0.0)		
Total citation of references			0.0004***	−0.0007***			−4.5 10^{-5}***	−4.8 10^{-6}***
			(0.0)	(0.0)			(1.35 10^{-7})	(1.36 10^{-7})
Control variables								
#Citation		0.554***		0.5491***		0.0002***		0.0001***
		(0.0005)		(0.0005)		(0.0)		(0.0)
Team size	0.0285**	−0.0245***	0.0457***	−0.0568***	−0.0003***	−0.0004***	−0.0006***	−0.0006***
	(0.0112)	(0.0055)	(0.0112)	(0.0056)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
First-citation year lag	−0.2913***	0.1465***	−0.2974***	0.1665***	0.007***	0.0071***	0.0074***	0.0075***
	(0.0097)	(0.0048)	(0.0097)	(0.0048)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Constant	2.0 10^{9}	9.03 10^{8}	6.1374***	−1.0144***	3.3 10^{8}**	3.5 10^{8}**	0.0804***	0.0789***
	(1.5 10^{10})	(7.46 10^{9})	(0.1333)	(0.0665)	(1.4 10^{8})	(1.4 10^{8})	(0.0013)	(0.0013)
Journal FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	463,348	463,348	463,348	463,348	463,348	463,348	463,348	463,348
R^2	0.028	0.766	0.028	0.760	0.075	0.076	0.057	0.057

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$. Note that if we do not control for the number of citations, the coefficient of the number of references to the disruptive citation is 0.0846 ($p<0.001$). This means that citing more references may increase the final disruptive citation. This result is intuitive and inspiring, as it suggests that a researcher cannot manipulate the disruptive citation of their paper by merely citing fewer or less cited papers.

long-term SDC and SCC (at the 40-year mark). To achieve this, we utilized a subnet of the whole citation network for each year and each laureate.

As depicted in Fig. 8, the majority of successful scientists acquired most of their disruptive and consolidating citation during the latter half of their careers, after passing their hot streaks stage (Liu et al., 2018; Zhao, Bu, & Li, 2021) and achieving high academic reputations. Notably, successful scientists tend to accumulate their SDC at an early age, while their SCC tend to form a lagging growth model.

Although in the most career years, the disruptive impact of these prominent scientists is lower than their consolidating impact, the gap between the two types of impact increases with each year (as can be observed in the inset of Fig. 8a). However, it can be observed that at a very early stage (about 1–3 years), their disruptive impact is actually higher than their consolidating impact. This result demonstrates, to some extent, that disruptive impact metrics can help predict successful scientists at an early stage and provides insights into the growth track for scientists. These findings may also suggest the importance of early-career innovation and disruption for future success in science.

This study contributes to our understanding of the dual impact of scientists and the determinants of successful scientific careers.

The findings suggest that disruptive impact metrics can help predict successful scientists at an early stage, while consolidating impact metrics tend to form a lagging growth model. Therefore, early-career innovation and disruption are important for future success in science.

7.3. Resistance to manipulation

In this section, we address the potential issue of researchers manipulating the disruptive citation or the CD-index by altering their referencing strategies. It seems plausible that an individual researcher could exert some influence on their disruptive citation since these citations are heavily dependent on the references cited in the focal paper. For instance, a researcher could artificially inflate their disruptive citation by citing references with minimal citation or by citing fewer references or even omitting references altogether. This raises the concern that the proposed measures in this study may be inadequate.

To investigate this issue, we conducted a paper-level analysis examining the effect of the quantity and overall influence of the focal paper's references on disruptive citation and the CD-index. We hypothesized that if researchers could manipulate disruptive citation or the CD-index by modifying their referencing strategies, the regression effect would be negative. In order to test this hypothesis, we utilized the Ordinary Least Squares (OLS) model, controlling for team size (Jones, Wuchty, & Uzzi, 2008; Wu et al., 2019), the first-citation year lag (Ke, Ferrara, Radicchi, & Flammini, 2015; Min, Bu, Wu, Ding, & Zhang, 2021), and accounting for variations in research fields and years by incorporating journal and year fixed effects. We employed OLS regressions to examine the relationship between the number of references and disruptive citation.

Our results, presented in Table 3, reveal that the number of references has a positive and significant effect on disruptive citation (model 1, coefficient $= 0.0846$, $p < 0.001$), suggesting that an increase in the number of references cited in a paper leads to higher disruptive citation. Thus, deliberately reducing the number of references cited in a paper may decrease disruptive citation. The negative effect of the number of references on the disruptive citation is only observed when comparing papers with the same citation count (model 2, coefficient $= -0.2239$, $p < 0.001$). We observe similar results in models (3) and (4), indicating that intentionally citing lower-cited papers does not lead to a decrease in disruptive citation (coefficient $= 0.0004$, $p < 0.001$). This implies that there is no evidence to suggest that researchers can manipulate the disruptive citation by intentionally citing fewer or less cited references.

Contrastingly, we observe a markedly different outcome for the CD-index. Our results indicate that a researcher can manipulate the CD-index of a single paper by citing fewer references. Regardless of whether we control for citation count (models 5 and 6), the effect of the number of references on the CD-index is approximately -0.003. While citing less impactful papers can also manipulate the CD-index, this strategy is considerably less efficient, as the coefficient is nearly zero, albeit significant (models 7 and 8).

This finding indicates that the CD-index may not be a reliable indicator of a scientist's disruptive impact if they intentionally cite fewer references in their work (Bornmann, Devarakonda, Tekles, & Chacko, 2020b; Ruan et al., 2021), as this could lead to an artificially inflated CD-index that misrepresents the scientist's actual disruptive impact. On the other hand, the disruptive citation appears to be less susceptible to such manipulation, providing a more accurate representation of a scientist's disruptive impact. These findings confirm the robustness of our metric against manipulation and emphasize the superiority of the disruptive citation as a measure of a scientist's disruptive impact, over the initial CD-index. It is worth noting that the number of references has a positive and significant effect on disruptive citation. This finding suggests that citing more references may help researchers gain more citations and increase their disruptive impact. Citing a large number of relevant references shows that the researcher has done a thorough review of the relevant literature, making their work more likely to be perceived as rigorous and comprehensive. Furthermore, citing more references provides readers with a larger pool of related works to draw from, increasing the likelihood that they will cite the focal paper in their own work.

8. Discussion and conclusion

8.1. Theoretical implications

This paper makes significant theoretical contributions in several ways. First, it proposes a novel approach to measuring the impact of scientists by extending the disruptive index from the paper level (Funk & Owen-Smith, 2017; Park et al., 2023; Wu et al., 2019) to the author level (Dorogovtsev & Mendes, 2015). This approach employs a set of metrics including the Scientists' Disruptive Citation (SDC) and Disruptive h-index (D h-index), which outperform other benchmark measures such as traditional metrics, normalized metrics, and recently proposed metrics (Wei et al., 2023). The study's empirical analysis provides important insights into the evaluation of scientific impact and the development of policies aimed at promoting scientific innovation. The proposed metrics can serve as reliable measures of scientific impact, highlighting the importance of disruptive research in advancing science and providing a more comprehensive and accurate measure of scientists' contributions to their fields.

Second, the study constructs a dual measurement framework that characterizes the impact of scientists from both a disruptive and consolidating perspective (Bu et al., 2021; Chen et al., 2021), providing new methods and perspectives for academic evaluation and performance assessment. This approach classifies scientists into two academic features, distinguishing between disruptive and consolidating scientists and enhancing the rationality of evaluating scientists' innovative level and potential (Hofstra et al., 2020). This framework highlights the importance of disruptive research in advancing science and sheds light on the diverse career paths of scientists. It may also serve as a useful reference for policymakers, funding agencies, and researchers seeking to improve scientific productivity.

Third, our study contributes to the existing literature on the limitations of the CD-index by acknowledging its susceptibility to

manipulation. Several previous studies (Leydesdorff & Bornmann, 2021; Leydesdorff et al., 2021; Ruan et al., 2021) have highlighted the potential for researchers to manipulate the CD-index by citing fewer references, which can artificially inflate the index and misrepresent the actual disruptive impact of the scientist or paper. This issue is particularly concerning since the CD-index has been widely used as a measure of disruptive impact in recent years (Park et al., 2023; Wei et al., 2023; Wu et al., 2022, 2019). In contrast, our study finds that the disruptive citation proposed in this study is less susceptible to manipulation, making it a more reliable metric for assessing a scientist's or a single paper's disruptive impact than the CD-index. While it is still possible for researchers to manipulate their disruptive citation by citing specific references, the influence of such manipulation is limited due to the heavy reliance of disruptive citation on the references cited in the focal paper. Furthermore, our paper-level analysis indicates that deliberately reducing the number of references cited in a paper may actually decrease disruptive citation. The susceptibility of citation-based metrics to manipulation is an ongoing concern in the field of scientometrics (Waltman, 2016; Waltman & Van Eck, 2012), and our study provides important insights into this issue. By highlighting the limitations of the CD-index and proposing the disruptive citation as a more robust metric for measuring disruptive impact, we contribute to the development of more reliable and accurate measures of scientific impact. This has important implications for the evaluation of scientific performance and the development of policies aimed at promoting scientific innovation (Hofstra et al., 2020). Ultimately, the development of more accurate and reliable metrics will benefit both individual researchers and the scientific community as a whole, by helping to identify and support the most innovative and impactful scientific research.

Fourth, this paper contributes to the research community by providing new datasets of disambiguated authors and laureates in the field of Physics (see Data Availability). These datasets can aid future studies in this field and facilitate the development of new approaches to measuring scientific impact and evaluating performance. Besides, the study proposes new ways to assess the consistency and convergent validity of novel metrics (Bornmann & Tekles, 2021), which can be useful in evaluating new metrics in the future (Lehmann, Jackson, & Lautrup, 2006).

Finally, the study's findings indicate that the SDC and D h-index are robust metrics for measuring scientists' innovative impact and academic standing, while the consolidating impact (SCC and C h-index) may reflect the influence foam of the total impact of a scientist. These insights have significant implications for the evaluation of scientific impact and the development of policies aimed at promoting scientific innovation. By prioritizing disruptive impact, policymakers and funding agencies can better identify and support scientists who are more likely to make groundbreaking discoveries and push the boundaries of their fields.

8.2. Practical implications

The practical implications of this study are significant for the evaluation and performance assessment of scientists. First, the introduction of new metrics, such as the Scientists' Disruptive Citation (SDC) and Disruptive h-index (D h-index), can provide a more accurate and comprehensive measure of scientists' innovative research (Acemoglu, Akcigit, & Kerr, 2016; Ding & Cronin, 2011). These metrics capture the disruptive impact of scientists and can identify scientists who are likely to make groundbreaking discoveries and push the boundaries of their fields. This is important because traditional metrics, such as total citation and h-index, may not capture the disruptive impact of scientists, which is essential for promoting scientific innovation (Brito & Navarro, 2021). Therefore, the use of these new metrics can aid in the identification and promotion of scientists who are more likely to contribute significantly to their fields (Zeng, Fan, Di, Wang, & Havlin, 2022).

Second, the condensed classification of scientists into disruptive and consolidating scientists provides a useful framework for identifying potential prominent scientists in their early careers (Sinatra et al., 2016), before their hot streaks (Liu et al., 2018; Zhao et al., 2021). As observed in the study, prominent scientists tend to accumulate their disruptive citation at an early age, while their consolidating citation tend to form a lagging growth model. Therefore, early-career innovation and disruption may be essential for future success in science (Foster et al., 2015; Yin et al., 2019). The use of this framework can aid in identifying promising scientists and investing in their potential early in their careers.

Third, the dual measurement system of disruptive and consolidating influence offers a more comprehensive and nuanced evaluation of scientists' impact, which can guide decision-making processes related to funding, hiring, and promotions. This approach provides a more accurate assessment of scientists' contributions to their fields, which can lead to more informed decision-making processes (Fortunato et al., 2018; Foster et al., 2015; Hofstra et al., 2020). Policymakers, funding agencies, and academic institutions can use this framework to evaluate the impact of scientists and promote scientific innovation.

Overall, the practical implications of this study can help to improve the accuracy and fairness of academic evaluation and decision-making processes. The use of new metrics, such as the SDC and D h-index, and the dual measurement system of disruptive and consolidating influence can aid in identifying and promoting scientists who are more likely to make significant contributions to their fields. The identification of promising scientists early in their careers can also lead to more informed investments in their potential. Therefore, the findings of this study have significant implications for the evaluation and performance assessment of scientists and the promotion of scientific innovation.

9. Conclusion

In summary, this study proposed a novel approach to quantifying scientists' disruptive and consolidating influence and demonstrated its validity and efficacy through empirical analysis. By introducing the dual evaluation framework of disruptive and consolidating influence, we have provided a new way to measure scientists that is scientifically sound, consistent, effective, feasible, and reasonable. Our findings shed light on the importance of considering both aspects of scientific impact and offer insights into identifying

Table A1
The descriptive statistics of each metric for laureates and non-laureates, respectively.

Laureates											
	Pub.	H	T. Cit.	SDC	SCC	D h	C h	Total CD	Total C	Total D	Citation-CD P
Sample Size	130	130	130	130	130	130	130	130	130	130	130
Mean	52.45	18.35	2151.08	1078.24	1072.84	12.25	13.8	2.50	4.59	2.09	27.87
Std	48.51	11.93	2963.57	1552.51	1589.57	7.85	9.37	3.92	4.64	1.71	24.71
Min	5	3	102	15	20	2	2	−3.85	0.04	0.07	2.50
25%	20	9	316.75	143.75	166.25	6	7	0.05	1.36	0.72	11.11
50%	42	17	1162.5	536	510	10.5	12	0.97	3.06	1.64	21.76
75%	63	24	2416.75	1229.5	1254.25	15.75	17.75	4.19	6.02	2.89	34.05
Max	307	58	15,906	9361	8744	42	47	21.21	24.87	7.87	153.01
Non-Laureate											
	Pub.	H	T. Cit.	SDC	SCC	D h	C h	Total CD	Total C	Total D	Citation-CD P
Sample Size	233,956	233,956	233,956	233,956	233,956	233,956	233,956	233,956	233,956	233,956	233,956
Mean	5.83	2.48	60	20.52	39.49	1.4	2.08	0.06	0.21	0.15	2.96
Std	12.39	3.18	218	85	142.54	1.79	2.69	0.45	0.60	0.37	6.24
Min	1	0	0	0	0	0	0	−5.09	0.00	0.00	0.00
25%	1	1	2	0	1	0	1	−0.04	0.00	0.00	0.50
50%	2	1	9	2	5	1	1	0.00	0.01	0.02	1.00
75%	5	3	36	11	24	2	3	0.00	0.11	0.12	2.50
Max	491	53	10,494	4089	7408	29	46	18.06	25.24	17.98	246.10

Table A2
The top scientists with the highest disruptive impact (D h-index) and consolidating impact (C h-index), respectively.

Top 5 Scientists with the highest disruptive impact (D h-Index)								
Scientists	Pub.	H	T. Cit.	SDC	SCC	D h	C h	Prize
Philip W. Anderson	138	55	13,920	9091	4829	42	37	Nobel
Steven Weinberg	133	58	12,435	6286	6149	40	43	Nobel
Patrick A. Lee	203	57	13,564	4820	8744	36	47	Dirac
Chen Ning Yang	107	41	6784	4183	2601	33	28	Nobel
Bertrand I. Halperin	185	56	12,470	4646	7824	32	47	Wolf
Top 5 Scientists with the highest consolidating impact (C h-Index)								
Scientists	Pub.	H	T. Cit.	SDC	SCC	D h	C h	Prize
Bertrand I. Halperin	185	56	12,470	4646	7824	32	47	Wolf
Patrick A. Lee	203	57	13,564	4820	8744	36	47	Dirac
Loren N. Pfeiffer	331	51	7788	1575	6213	21	46	None
Kenneth W. West	253	49	7009	1401	5608	20	44	None
Steven Weinberg	133	58	12,435	6286	6149	40	43	Nobel

innovative scientists, reforming performance and reward systems, reviewing and evaluating funding projects, and formulating research incentive policies. Overall, this study contributes to a better understanding of the scientific evaluation process and paves the way for further research in this area.

However, there are still several limitations that need to be addressed in future research. First, the sample used in this study is limited to the APS dataset, which may not be representative of all scientists (Wang et al., 2023). Second, this article has only focused on Physics, and future research should explore whether the same patterns apply to other fields such as natural sciences, social sciences, and interdisciplinary fields. Third, although this study explored the resistance to manipulation of the disruptive citation, the positive effect of the number of references on the disruptive citation remains to be addressed.

In order to address the limitations of this study, future research should focus on expanding the sample size and including datasets from more diverse fields. For instance, the MAG dataset (Wang et al., 2020) could be considered as a more comprehensive source. Additionally, advanced computing technologies can be used to handle the high calculation complexity of deep metrics. Furthermore, future research can investigate the influence mode of scientists with different academic characteristics and consider different citation time windows for effective comparison of scientists' influence in different years. Besides, it would be interesting to explore whether the proposed disruptive and consolidating influence measurement framework for scientists is applicable to other fields such as natural sciences, social sciences, and interdisciplinary fields. Lastly, the concept of disruptiveness and consolidation can also be extended to higher aggregated levels beyond the scientists' level, such as journals, research teams, academic institutions, and even countries.

CRediT authorship contribution statement

Alex J. Yang: Writing-original draft, Conceptualization, Methodology, Software, Data visualization, Validation, Data curation.

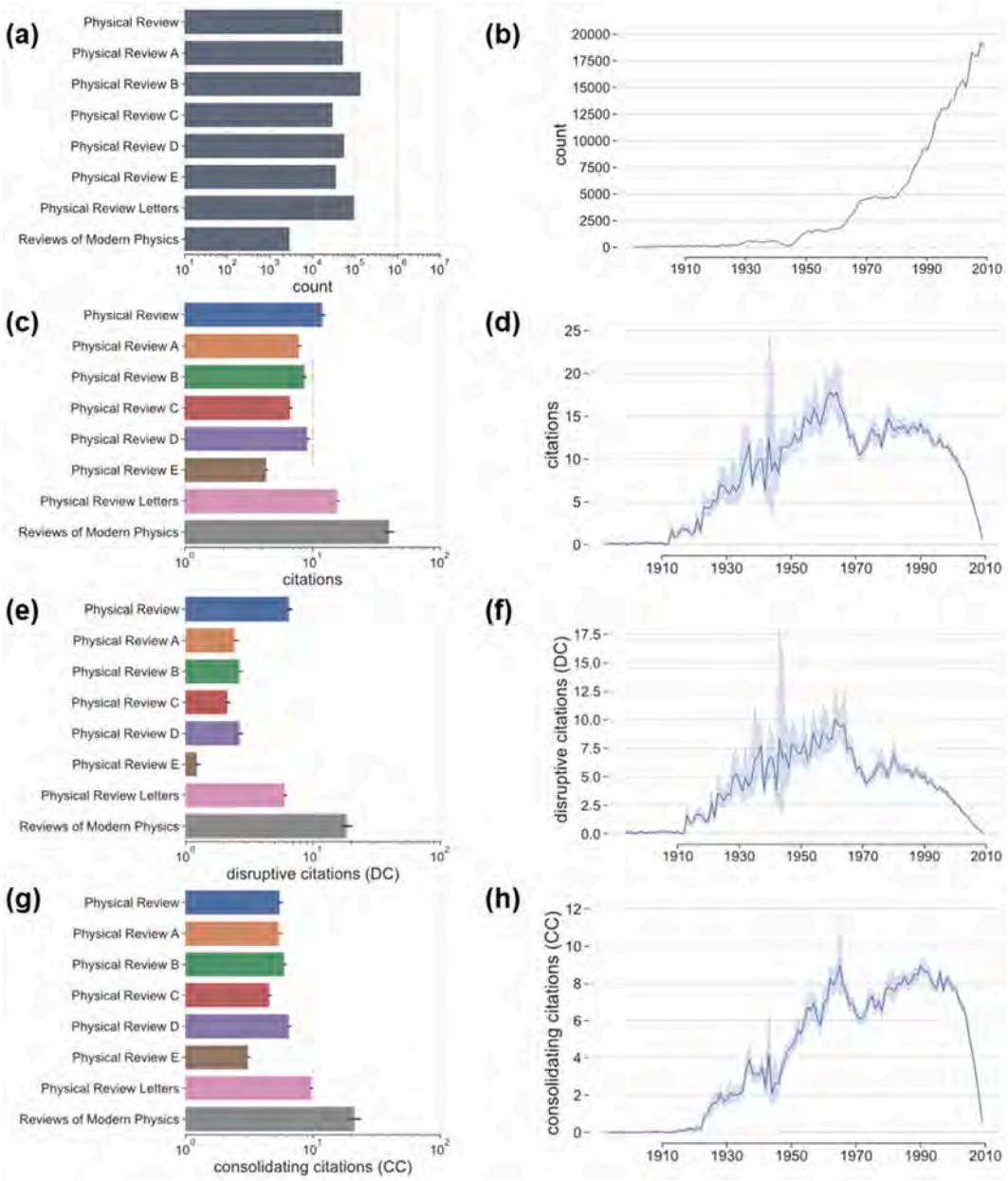


Fig. B1. APS dataset description. Paper-level distributions of (a-b) the number of publications, (c-d) citation count, (e-f) disruptive citation, and (g-h) consolidating citation across journals and years are presented. The error bars in the left panels indicate the standard error, while the shaded areas in the right panels represent the 95% confidence interval.

Haotian Hu: Data collection, Writing- review & editing, Validation. **Yuehua Zhao**: Conceptualization, Methodology, Writing- review & editing. **Hao Wang**: Writing- review & editing, Supervision. **Sanhong Deng**: Conceptualization, Methodology, Writing-review & editing, Supervision.

Data availability

We are happy to share our data with the scientific community. The citation data used in this study can be obtained by making reasonable requests. The APS citation dataset is available at https://journals.aps.org/datasets, while the Physics Tree data can be accessed at https://academictree.org/physics/. Information on laureates can be obtained from the official websites of the Nobel Prize in Physics (https://www.nobelprize.org/prizes/physics/), the Nobel Prize in Chemistry (https://www.nobelprize.org/prizes/chemistry/), the Wolf Prize (https://wolffund.org.il/home-page/), and the Dirac Medal (https://www.ictp.it/prize/dirac-medal).

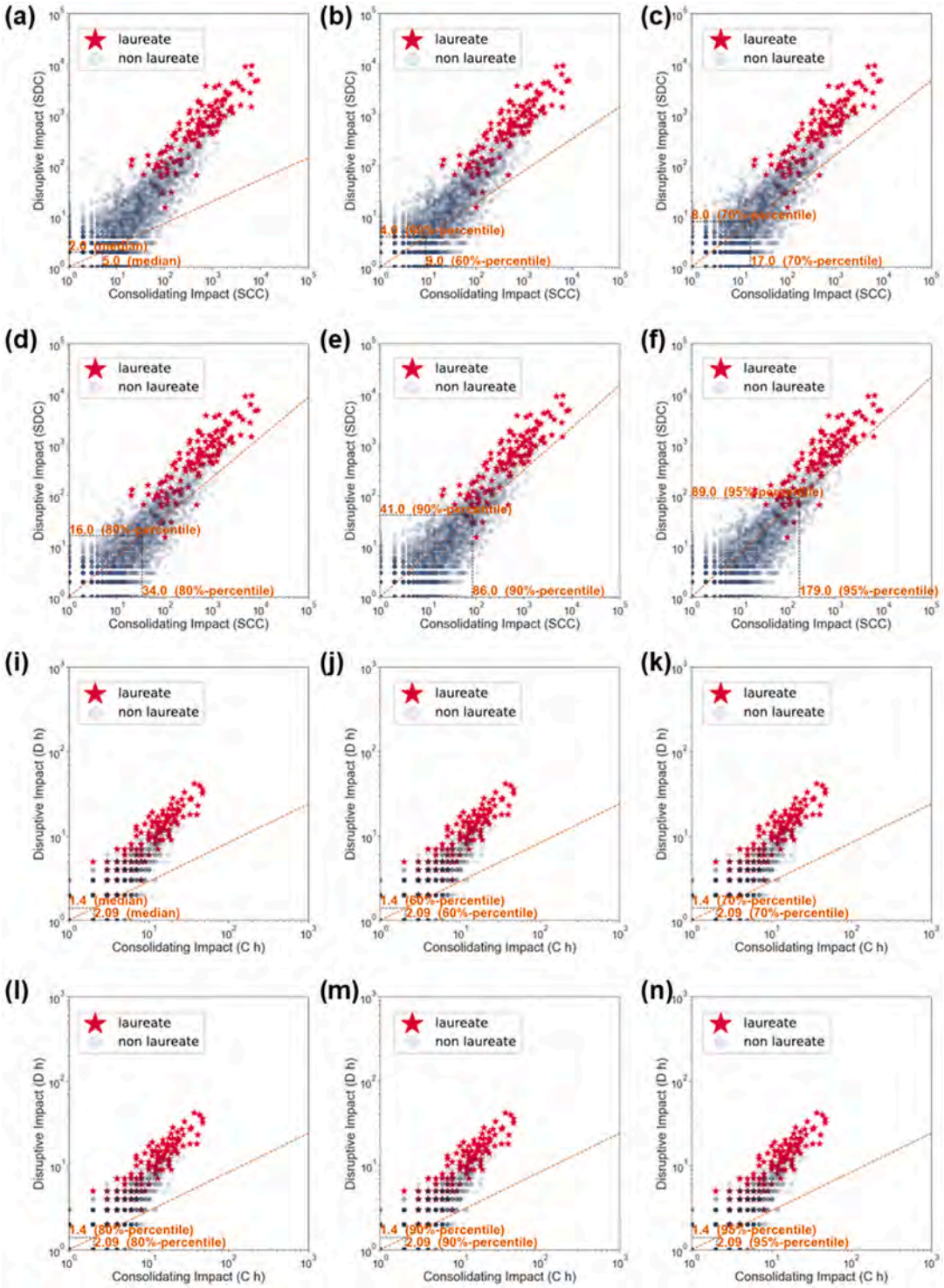


Fig. B2. The dual evaluation framework is robust under different thresholds. The red pentagram represents the laureates, and the blue circle refers to the non-laureates; the blue dashed line represents the mean value, and the green dashed line means the dividing line. The data on both the horizontal and vertical axes are commonly processed using logarithms (log10). **(a-f)** Disruptive scientists and consolidating scientists based on SDC and SCC, where we vary the critical values from the 50th to 95th percentiles. **(i-n)** Disruptive scientists and consolidating scientists based on D h-index and C h-index, where we vary the critical values from the 50th to 95th percentiles. Note that we have not displayed the percentiles below the 50th as the critical value should be greater than 1, while the 40th percentile of SDC does not meet this criterion.

We also would like to share the disambiguated author data for APS, which includes all the metrics and a column indicating whether the author is a laureate or non-laureate: https://github.com/AlexJieYang/Disambiguated-authors-for-APS-datasets.

Code availability

The code is available at https://github.com/AlexJieYang/SDC-SCC.

Declaration of Competing Interest

The authors declare no competing interest relevant to this article.

Acknowledgments

The authors would like to thank two anonymous reviewers for valuable advises. This research was supported by the National Social Science Fund of China (No.19BTQ062), the International Joint Informatics Laboratory Fund, and the Fundamental Research Funds for the Central Universities.

Appendix A. Table

Table A1,Table A2.

Appendix B. Figure

Fig. B1,Fig. B2.

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