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Research Paper

Quantifying delayed recognition of scientists

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ABSTRACT

Delayed recognition is a significant phenomenon with implications for career advancement, funding opportunities, and the dissemination of scientific knowledge. Despite its importance, most studies have focused on delayed recognition at the paper level, leaving a gap in understanding how this phenomenon unfolds at the level of individual scientists. This paper presents a novel framework for quantifying delayed recognition in scientists by analyzing their career-level citation trajectories. The framework utilizes two key metrics—the author beauty coefficient (***AB***) and author career awakening time ($A_{t\alpha}$)—to capture the temporal dynamics of a scientist's citation impact over the course of their career. Our analysis demonstrates that these metrics reveal patterns distinct from paper-level measures, with no significant correlation to averaged paper delayed recognition scores. Fixed-effect regression analyses indicate that female scientists and those pursuing novel or disruptive research experience greater delays in recognition. Additionally, through Coarsened Exact Matching (CEM) analysis, we find that scientists in smaller groups exhibit higher survival rates in academia but also face more significant delayed recognition. This paper delivers a fresh methodological approach and critical insights into the demographic and research factors driving delayed recognition, enhancing our understanding of scientific impact at the individual level.

1. Introduction

Scientific recognition plays a crucial role in advancing a researcher's career, influencing opportunities for funding, collaboration, and academic progress (Andalón et al., 2024; Azoulay et al., 2011; Guo et al., 2024; Li et al., 2024; Liu et al., 2021; Shi et al., 2023; Xing et al., 2025). In many scientific fields, recognition typically follows a pattern marked by citation counts, which serve as a measure of a scholar's influence and the impact of their work (Fortunato et al., 2018; Liu et al., 2023). However, this recognition is often delayed, with a scientist's contributions sometimes gaining significant attention years after their initial publication (Garfield, 1989; Ke et al., 2015; Yang, Zhao et al., 2024). This phenomenon of delayed recognition is not just an individual experience; it is systemic, affecting the way scientific knowledge spreads, how ideas are adopted, and how careers evolve. Despite its importance, the study of delayed recognition has predominantly focused on individual papers rather than the scientists themselves. Metrics like the beauty coefficient (Ke et al., 2015), which quantifies citation delays at the paper level, have illuminated how specific works can languish before achieving prominence. However, this approach overlooks the broader career context in which scientists operate—a context shaped by cumulative output, evolving impact, and external factors such as gender, research style, and collaboration dynamics. Understanding delayed recognition at the scientist level is critical, as it offers a more holistic view of how recognition unfolds over a career and reveals

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disparities that paper-level analyses might miss.

This paper addresses this gap by introducing a novel framework to quantify delayed recognition at the individual scientist level. Using career-long citation trajectories from the Microsoft Academic Graph (MAG) dataset, we develop two key metrics: the author beauty coefficient ($\boldsymbol{AB}$) and the author career awakening time ($\boldsymbol{A_{t\alpha}}$). These measures capture the temporal dynamics of a scientist's impact, from periods of obscurity to eventual acknowledgment, and allow us to explore how recognition patterns differ from those observed at the paper level. We also use rescaling method to propose the field and time universal distribution measures. We demonstrate that our scientist-level framework reveals distinct dimensions of delayed recognition, uncorrelated with averaged paper-level metrics, thus providing a complementary perspective on scientific impact.

Our analysis, based on a sample of 1.679 million scientists with careers spanning 1970 to 2021, uncovers significant patterns. Regression analyses reveal that female scientists and those engaged in novel or disruptive research experience greater delays in recognition, even after controlling for career factors such as productivity and total citations. Furthermore, using Coarsened Exact Matching (CEM), we find that scientists trained in small academic groups—often linked to innovative, paradigm-challenging work (Wu et al., 2019)—are more likely to persist in academia but face heightened delayed recognition compared to their large-group counterparts. These findings highlight structural and research-related factors that shape recognition timelines, offering new insights into the dynamics of scientific careers.

This study contributes to the literature in three key ways. First, it provides a methodological advancement by extending delayed recognition analysis from papers to scientists, supported by robust, parameter-free metrics. Second, it identifies demographic and research characteristics—gender, novelty, disruption, and group size—as drivers of delayed recognition, with implications for equity and innovation in science. Third, it leverages a comprehensive dataset and rigorous statistical methods to ensure generalizable conclusions. By reframing delayed recognition as a career-level phenomenon, this paper not only deepens our understanding of scientific impact but also informs policies to support scientists whose contributions may otherwise go unrecognized for too long.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature, situating our work within existing research on recognition dynamics. Section 3 describes the data sources and preprocessing steps. Section 4 details our methodological approach for measuring delayed recognition at the career level. Section 5 presents our empirical findings, including gender disparities and the role of research novelty. Section 6 explores the impact of academic group size on recognition timing. Section 7 discusses key implications, study limitations, and directions for future research.

2. Literature review

2.1. Delayed recognition of papers

Delayed recognition at the paper level refers to the phenomenon where scientific publications receive minimal citations or acknowledgment in the years immediately following their publication but gain substantial attention and impact after an extended period (Garfield, 1980; Glänzel et al., 2003). This temporal gap between the dissemination of research findings and their eventual recognition highlights the non-linear nature of scientific influence. Various studies have conceptualized this phenomenon using terms such as "Resisted Discoveries" (Barber, 1961), "Late-bloomers" (Merton, 1979), and the "Mendel Syndrome" (O'Reilly et al., 1994). In recent decades, such publications have been commonly referred to as "Sleeping Beauties" (van Raan, 2004)—papers that lie dormant for years before experiencing a significant surge in citations and scholarly attention. These atypical citation trajectories, which deviate from conventional patterns, are identified as one of the "seven myths in bibliometrics" (Glanzel & Garfield, 2004), underscoring their relevance in the study of scientific impact.

van Raan (2004) was among the first to systematically examine delayed recognition at the paper level, introducing three core criteria—depth of sleep, length of sleep, and awakening intensity—to identify sleeping beauties. His work laid the foundation for subsequent research, demonstrating that analyzing delayed recognition can uncover transformative research and provide valuable insights into the dynamics of a paper's impact trajectory (Miura et al., 2023; Yang, Zhao et al., 2024). Efforts to develop quantitative criteria for studying delayed recognition have yielded three main approaches: average-based, quartile-based, and parameter-free measures. van Raan's original framework employed an average-based criterion, defining sleeping beauties as papers that remain unnoticed for a prolonged period before experiencing a sharp rise in citations. Costas et al. (2010) later introduced a quartile-based measure that identifies delayed recognition by pinpointing the year in which an article first accumulates at least half of its total citations. To address these limitations, Ke et al. (2015) proposed a parameter-free index known as the Beauty Coefficient. This metric evaluates a paper's delayed recognition by comparing its actual citation trajectory to a reference line spanning from its publication year to its peak citation year. The parameter-free approach stands out for its ability to bypass subjective thresholds and arbitrary assumptions, offering an objective and reproducible method for assessing delayed recognition (Wang & Barabási, 2021).

Despite the extensive research on delayed recognition at the paper level, similar studies at the scientist level remain notably absent. This gap likely stems from the significant challenges associated with constructing career-level datasets. While dynamic citation data for individual papers is relatively accessible, compiling comprehensive author-level citation trajectories requires overcoming considerable logistical and methodological hurdles (Liu et al., 2023). Consequently, understanding delayed recognition at the scientist level remains an open avenue for exploration, with the potential to provide new insights into career dynamics and the acknowledgment of scientific contributions over time.

2.2. The dynamic of scientists' career

Existing research on the dynamics of scientists' careers often focuses on the sequence of publications produced by individuals, analyzing the characteristics and impacts of their works over time. Some researchers have used career-level datasets to analyze broader features such as mobility, collaboration, and mentorship. Sun et al. (2023) found that mobility within academic rankings is notably low, especially for the top- and bottom-ranked authors, with this stability persisting throughout their careers. Li et al. (2022) developed models to disentangle the network effects of productivity and prominence, highlighting gendered differences in these dimensions for mid-career researchers.

Several studies investigate the success dynamics of individual papers within a scientist's career. For example, Sinatra et al. (2016) analyzed the impact and productivity trends of scientists, revealing that the distribution of influential publications is random across a researcher's career. Their stochastic model uncouples the effects of productivity, individual ability, and luck, unveiling universal patterns governing scientific success. Similarly, (Liu et al., 2021, 2018) examined large-scale career histories, tracing scientists' publication records to reveal that high-impact works, or "hit" publications, often occur in bursts of productivity. Their observations are explained through a "hot-streak" model, indicating that periods of sustained success are a key feature of many scientific careers.

Another stream of literature explores the dynamics of scientists' research interests over time. Jia et al. (2017) conducted a large-scale analysis of publication records, showing that changes in research interests follow a reproducible pattern characterized by an exponential distribution. This pattern reflects a balance between exploiting familiar topics and exploring new areas of inquiry. Similarly, Zeng et al. (2019) analyzed topic-switching behaviors, demonstrating that the co-citation networks of a scientist's work often exhibit distinct community structures, with each major community corresponding to a focused research theme. These studies highlight how shifts in focus and topic influence scientific trajectories and career impact.

A third line of inquiry examines the impact of various factors on the success or failure of scientific careers. For example, Kaminski and Geisler (2012) performed a survival analysis of science and engineering faculty, finding that the median retention time in academia is just over ten years, with $<$50 % of faculty remaining in their positions long-term. Yin et al. (2019) used large-scale career data to identify early signals of success or failure, revealing dynamics that differentiate successful careers from those that falter. Other studies focus on interdisciplinary research and its challenges. Berkes et al. (2024) explored the slow adoption of interdisciplinary research in biomedical sciences, finding that while interdisciplinary work is often impactful, it presents early career barriers that lead many researchers to exit academia. Similarly, Andalón et al. (2024) examined the effects of increasing team sizes in academic science, discovering that larger teams inadvertently disadvantage junior scientists by reducing their likelihood of securing funding or tenure, thereby increasing their chances of leaving academia.

In summary, the existing literature offers valuable insights into paper-level delayed recognition, the dynamics of scientific careers, and the factors influencing individual success. However, a significant gap remains in our understanding of how delayed recognition manifests at the level of individual scientists, particularly in relation to their career trajectories and the evolution of their research impact over time. While studies have explored the timing of high-impact publications, the shifting landscapes of research interests, and the systemic factors affecting career success, they have yet to comprehensively integrate these elements with the phenomenon of delayed recognition. Our study aims to bridge this gap by introducing a novel framework to quantify scientist-level delayed recognition, thereby providing a more holistic view of how scientific contributions are acknowledged and assimilated into the broader scientific discourse. By examining the career-long citation trajectories of scientists, we can uncover nuanced patterns that paper-level analyses and traditional career studies miss. This approach not only sheds light on the individual experiences of scientists but also offers a deeper understanding of the mechanisms that shape scientific progress, ultimately informing strategies to foster a more equitable and efficient scientific ecosystem.

3. Datasets

This study utilized the Microsoft Academic Graph (MAG) dataset (Wang et al., 2020), a comprehensive repository of scientific publications that includes bibliographic details, authorship, author affiliations, and citation networks. Covering a period from 1800 to 2021, MAG encompasses over 200 million documents, including journal articles, conference proceedings, preprints, and other types of research outputs. For this analysis, we focused on publications of all types, emphasizing author career-level data. This dataset provides both dynamic data, representing annual metrics for each scientist, and aggregated data, reflecting average values of specific publication characteristics across their careers.

MAG employs sophisticated machine learning algorithms to classify research fields, offering a hierarchical framework comprising 19 primary domains further subdivided into 292 subfields. For the purposes of this study, both the rescaling methods in Appendix and the fixed-effects analyses in Section 6 are based on the primary 19 fields. A scientist's primary field is determined by the field most frequently associated with their publications, with each scientist assigned a single primary domain.

Our primary dataset centers on author career trajectories, utilizing dynamic (yearly) citation data for all publications associated with each scientist. To address challenges such as name disambiguation, MAG employs advanced methodologies, including machine learning, crowdsourcing, and web-based resources like personal websites and curricula vitae. These methods have been shown to achieve high accuracy, as evidenced by Lin et al. (2023), who conducted a validation test demonstrating 100 % precision and 84 % recall for name disambiguation in MAG. This robust approach ensures the reliability of career and affiliation data for individual scientists. To infer gender, we employed a statistical model (Van Buskirk et al., 2023) based on first names, leveraging MAG's author data. This model utilizes a cultural consensus approach to associate names with gender probabilities. In our dataset, probabilities exceeding 0.5 were classified as female authors, while probabilities below 0.5 were categorized as male authors.

To refine our dataset, we included only scientists meeting specific criteria: at least 8 years of career duration and a minimum of 10 publications in MAG. This threshold excludes individuals with insufficient publication histories or short careers. To further ensure data quality, we excluded scientists with >500 publications to mitigate errors arising from potential misattributions during name disambiguation (Yang & Wang, 2024). Additionally, we focused on scientists whose careers began between 1970 and 2000, resulting in a final dataset comprising 1679,374 scientists.

4. Quantifying delayed recognition of scientists

4.1. Author beauty coefficient and awakening time

To quantify the phenomenon of delayed recognition among scientists, we adopt the framework proposed by Ke et al. (2015). This framework introduces a parameter-independent metric termed the beauty coefficient (***B***), which utilizes yearly citation dynamics at the paper level to assess the delayed recognition of influential research. Specifically, it evaluates the impact of scientific papers by analyzing their citation trajectories over time.

Building on this approach, we extend the method to focus on the career citation trajectories of individual scientists rather than individual publications. To achieve this, we first compile the publication data for each scientist. Subsequently, we aggregate the yearly citation counts for all publications by a given author, constructing a comprehensive career-level dynamic citation trajectory.

We define the author beauty coefficient (***AB***) as a systematic measure that evaluates the delayed recognition of scientists. This measure is derived by analyzing the career citation trajectory, taking into account the year a scientist commenced their career (i.e., the year of their first publication), the peak annual citation count achieved, and the year this peak was attained. The ***AB*** quantifies the divergence between actual citation trajectories and a hypothetical straight-line trajectory connecting the starting point and the peak citation point, thus illuminating patterns of deferred acknowledgment. Mathematically, the start-peak line L_t is expressed as:

$$L_t = \frac{c_{t_m} - c_0}{t_m} t + c_0,$$

where c_t represents the citations received in the t^{th} year after the first publication, t_m is the year of peak annual citations, and c_0 denotes the citation count in the first year of the scientist's career. The author beauty coefficient (***AB***) is calculated as the sum of normalized deviations between the observed citation trajectory and the start-peak line, for each year t up to t_m:

$$\boldsymbol{AB} = \sum_{t=0}^{t_m} \frac{\frac{c_{t_m} - c_0}{t_m} t + c_0 - c_t}{max\{1, c_t\}},$$

where $max\{1, c_t\}$ penalizes early citations, ensuring that higher values of ***AB*** correspond to citation trajectories with prolonged dormant periods followed by intense recognition. An ***AB*** value of zero corresponds to scientists with instantaneous peak citations ($t_m = 0$), negative values indicate concave citation trajectories, and positive values increase with the duration and intensity of the delayed recognition.

Additionally, we define the author career awakening time ($\boldsymbol{A_{t\alpha}}$) in a scientist's career citation trajectory as the year prior to t_m when the distance d_t between the actual trajectory and the start-peak line reaches its maximum. The distance d_t is computed as:

$$d_t = \frac{|(c_{t_m} - c_0)t - t_m c_t + t_m c_0|}{\sqrt{(ctm - c0)^2 + t_m^2}},$$

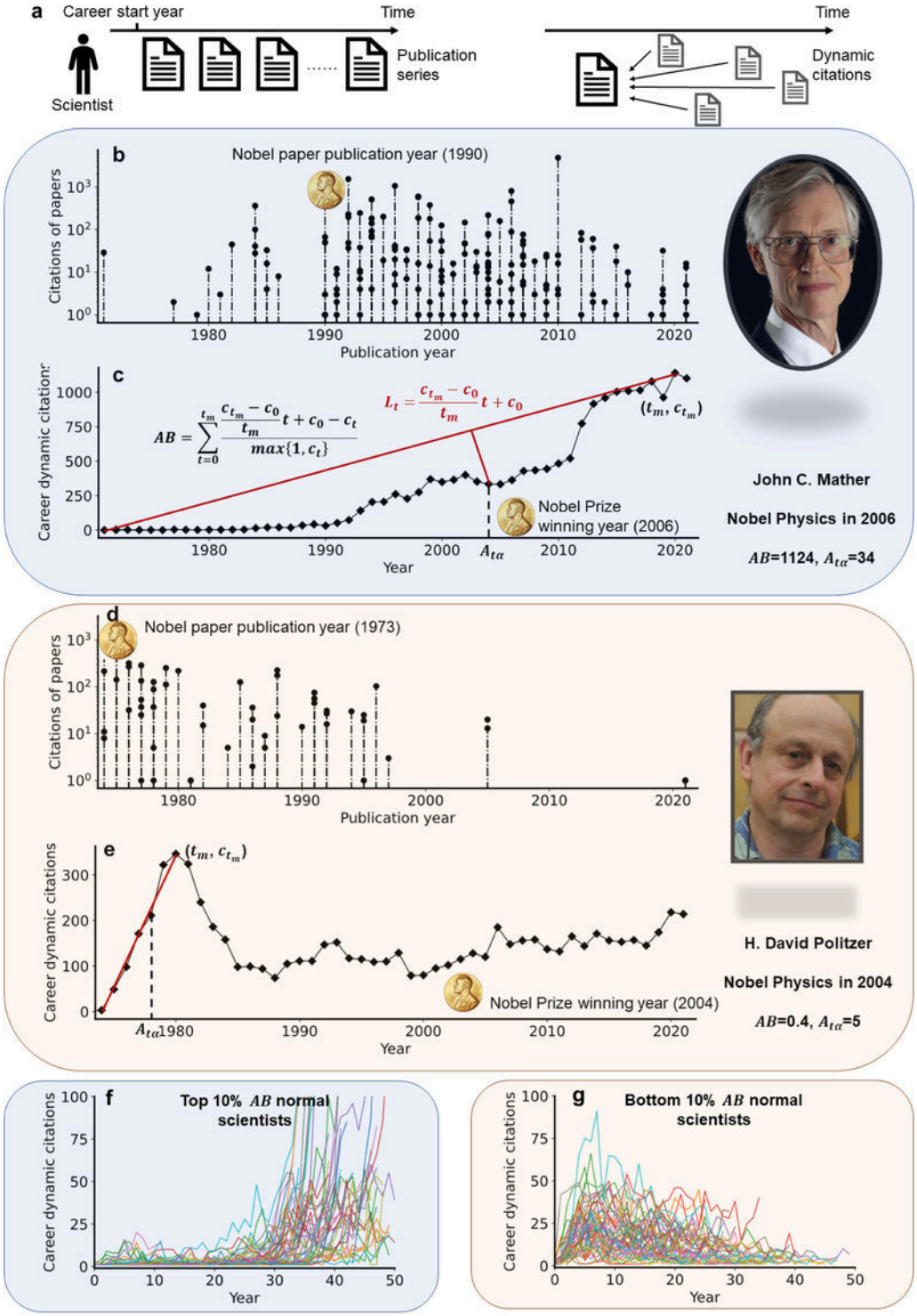
and the author career awakening time $\boldsymbol{A_{t\alpha}}$ is encapsulated by the expression:

$$\boldsymbol{A_{t\alpha}} = arg\{max_{t<t_m} d_t\}.$$

The author beauty coefficient (***AB***) offers a robust, parameter-free metric for quantifying the delayed recognition of scientists, encompassing their entire publication and citation history. The author career awakening time $t\alpha$ further provides a precise indication of the period when a scientist's work begins to garner heightened acknowledgment.

Fig. 1 illustrates our framework for measuring delayed recognition in scientists' careers, using Nobel laureates John C. Mather and H. David Politzer as case studies. The process begins by gathering yearly citation counts for all of a scientist's publications and combining them into a single career-level citation trajectory. This trajectory provides a clear view of how a scientist's impact evolves over time. From this, we calculate two key metrics: the author beauty coefficient (***AB***), which measures the extent of delayed recognition, and the author career awakening time ($\boldsymbol{A_{t\alpha}}$), which pinpoints when significant recognition begins.

John C. Mather, a physicist who earned his Ph.D. from the University of California, Berkeley in 1974, exemplifies delayed recognition. His career began in 1971, but his early work received little attention. In 1990, he published a groundbreaking paper (Mather et al., 1990), "A Preliminary Measurement of the Cosmic Microwave Background Spectrum by the Cosmic Background Explorer (COBE) Satellite," which provided evidence for the Big Bang theory by showing the universe originated from a hot, dense state over 10 billion years ago. This paper marked a turning point, boosting his recognition and leading to many high-impact publications thereafter. Our framework calculates Mather's author career awakening time ($\boldsymbol{A_{t\alpha}}$) as 34 years after 1971 (i.e., 2004), which is 14 years after his 1990 paper and just two year after he won the Nobel Prize in 2006. His author beauty coefficient (***AB***) is 1124, placing him in



(caption on next page)

Fig. 1. Framework for Quantifying Delayed Recognition in Scientists. (a) Overview of the method for building and analyzing a scientist's career-level citation trajectory, based on yearly citation data from all their publications. (b-c) Case study of a late bloomer: John C. Mather. (b) Total citation counts for all publications authored by John C. Mather. c) Aggregated citation trajectory showing yearly citation counts across Mather's career, derived from all his publications. This panel also illustrates the delayed recognition framework, calculating the author beauty coefficient (***AB***) and author career awakening time ($\boldsymbol{A_{t\alpha}}$). For Mather, $\boldsymbol{A_{t\alpha}} = 34$ years (2004), occurring 14 years after his Nobel-winning 1990 paper and 2 years before his 2006 Nobel Prize. (d-e) Case study of an early bloomer: H. David Politzer. (d) Total citation counts for all publications authored by H. David Politzer. (e) Aggregated citation trajectory for Politzer, with the framework applied to compute ***AB*** and $\boldsymbol{A_{t\alpha}}$, reflecting his early recognition pattern. For Politzer, $\boldsymbol{A_{t\alpha}} = 5$ years (1978), occurring 14 years after his Nobel-winning 1973 paper and 26 years before his 2004 Nobel Prize. (f-g) Career citation trajectories for 50 randomly selected "typical" scientists (total citations between 100 and 1000), split into two groups: (f) Top 10 % AB scores, indicating high delayed recognition. (g) Bottom 10 % AB scores, indicating low delayed recognition.

the top 1 % of our sample, reflecting a long period of low recognition followed by a dramatic rise.

In contrast, H. David Politzer experienced immediate recognition. His first paper (Politzer, 1973), "Reliable perturbative results for strong interactions?", published in 1973, introduced the concept of asymptotic freedom—showing that the strong force between quarks weakens as they get closer together. This work, which earned him the Nobel Prize in 2004, was his most impactful publication right from the start. His career citation trajectory rises steadily for the first 8 years but declines afterward. Politzer's author beauty coefficient (***AB***) is 0.4, in the bottom 1 % of our sample, indicating little to no delay in recognition.

To further demonstrate our framework, we analyzed "typical" scientists—those with total citations between 100 and 1000. We randomly selected two groups: one with author beauty coefficient (***AB***) scores in the top 10 % (high delayed recognition) and another in the bottom 10 % (low delayed recognition). Results in Figs. 1f–g reveal distinct patterns. Scientists with high ***AB*** scores have few citations early in their careers but see a surge later on, while those with low author beauty coefficient (***AB***) scores gain citations early and taper off over time. These contrasting trajectories highlight the effectiveness of our metrics in capturing delayed recognition across different career paths.

Note that author beauty coefficient (***AB***) and author career awakening time ($\boldsymbol{A_{t\alpha}}$), vary significantly across disciplines and career start years, as shown in Fig. A1. For example, in Medicine, scientists starting in 1971 have an average ***AB*** of 346 and $\boldsymbol{A_{t\alpha}}$ of 23 years, while those starting in 1999 show lower values of 107 and 12 years, respectively. These differences persist even after normalizing by total citations and career length, complicating cross-field and cross-cohort comparisons. To address this, we rescale ***AB*** and $\boldsymbol{A_{t\alpha}}$ relative to their category means (field and career start year), defining $\boldsymbol{AB_f} = \frac{AB}{\widetilde{AB}}$, and $\boldsymbol{A_{t\alpha f}} = \frac{A_{t\alpha}}{\widetilde{A_{t\alpha}}}$. This normalization aligns their distributions, which follow a universal lognormal pattern, enabling fair comparisons across disciplines and time periods. Rankings based on rescaled metrics ($\boldsymbol{AB_f}$ and $\boldsymbol{A_{t\alpha f}}$) show consistent distributions, unlike raw metrics, which exhibit significant bias (Figs. A2–A5). See Appendix A for detailed information.

4.2. Comparing scientist-level and paper-level delayed recognition measures

Given the focus of this paper, it's critical to compare our new scientist-level framework with the established paper-level framework (Ke et al., 2015) (i.e., paper beauty coefficient and awakening time). Many readers might assume that averaging paper-level metrics for a scientist's publications would adequately reflect their delayed recognition. Here, we demonstrate that this assumption does not hold.

We begin by examining the paper-level beauty coefficient and awakening time distributions for two Nobel laureates: late bloomer John C. Mather and early bloomer H. David Politzer. Intuitively, one might expect Mather, with his delayed career recognition, to have a higher average paper beauty coefficient and awakening time than Politzer, who gained recognition early. However, Fig. 2a–d reveals the opposite. Mather's average paper beauty coefficient is 3.9, and his average paper awakening time is 4.1 years, while Politzer's are 10.9 and 6.8 years, respectively. This counterintuitive result stems from a key difference: Mather published little in his early career, while Politzer produced many impactful papers early on. Paper-level metrics fail to capture this career-wide pattern, underscoring the value of our scientist-level measures.

Next, we compare the author beauty coefficient (***AB***) and average paper beauty coefficient across disciplines, using the 19 level-0 fields in MAG. Fig. 2e–f shows that both metrics vary widely across fields, but their patterns differ. Physicists, for example, have the highest average AB, indicating significant delayed recognition at the scientist level, yet their papers do not stand out for delayed recognition compared to other fields. Conversely, Philosophy papers have the highest average paper beauty coefficient, but philosophers as a group do not exhibit high AB scores. This discrepancy highlights how scientist-level and paper-level measures capture distinct dynamics. To explore this further, we analyzed the relationship between ***AB*** and average paper beauty coefficient for individual scientists. We converted both metrics into percentiles and plotted their relationship in Fig. 2 g, revealing an inverted-U shape. This suggests that scientists with moderate paper-level delayed recognition may experience the highest career-level delays, while those with very low or very high paper beauty coefficients show less delay at the scientist level. At the field level (using 292 level-1 MAG fields), in Fig. 2h, we found no significant linear correlation between aggregated AB and average paper beauty coefficient, reinforcing their independence.

Finally, we examined these metrics across regions in Figs. 2i–j, using affiliation data from MAG. Scientists in non-English-speaking, big-science nations like mainland China and India tend to have very high average ***AB*** scores, indicating pronounced career-level delayed recognition. In contrast, scientists in developed English-speaking countries, such as the USA, have much lower ***AB*** scores. However, paper-level patterns differ: Chinese scientists' papers have low beauty coefficients, while U.S. scientists' papers score higher. This divergence further illustrates that scientist-level delayed recognition cannot be inferred from paper-level measures alone.

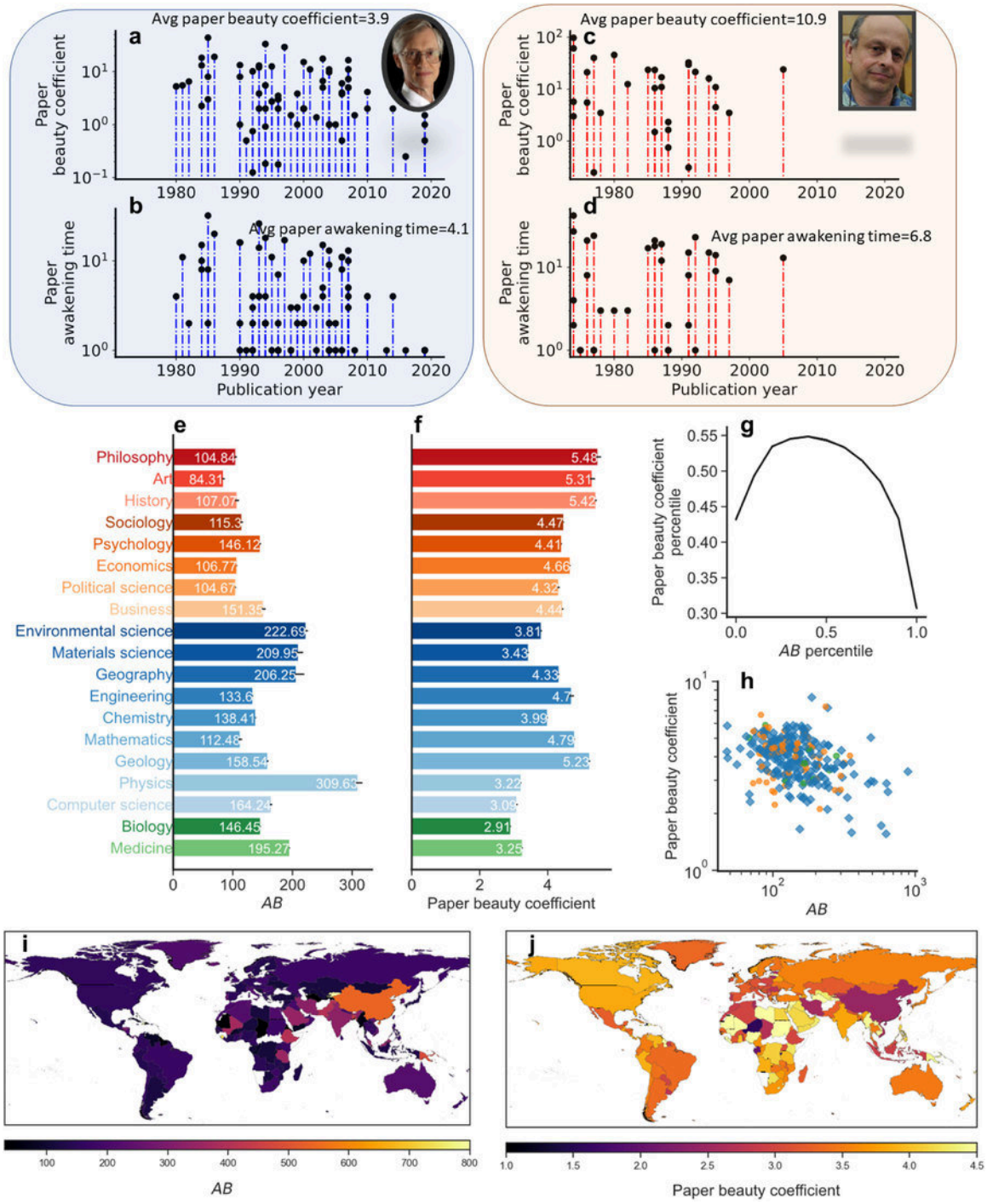


Fig. 2. Comparing Scientist-Level and Paper-Level Delayed Recognition Metrics. (a–d) Distribution of paper-level beauty coefficients (a, c) and awakening times (b, d) for Nobel laureates John C. Mather (late bloomer) and H. David Politzer (early bloomer). Panels a and b show Mather's average paper beauty coefficient (3.9) and awakening time (4.1 years), while c and d show Politzer's higher values (10.9 and 6.8 years). (e–f) Field-level comparison of author beauty coefficient (AB) and average paper beauty coefficient across the 19 level-0 fields in MAG. (g) Binned line plot of individual scientists' AB percentiles versus average paper beauty coefficient percentiles, displaying an inverted-U relationship. (h) Field-level scatter plot (292 level-1 MAG fields) of aggregated AB versus average paper beauty coefficient. (i–j) Regional comparison of delayed recognition metrics using MAG affiliation data. Panel i shows average AB scores by region, while panel j shows average paper beauty coefficients.

5. Delayed recognition and scientific innovation

In this section, we employ Ordinary Least Squares (OLS) regression to investigate gender differences in delayed recognition of scientists while controlling for potential confounding factors. Additionally, we construct a series of author-level characteristics to quantify the innovative potential of scientists. Using these metrics, we analyze the relationship between delayed recognition in science and the innovative potential of scientists.

5.1. Related metrics

We construct disruption and novelty of scientists based on the average disruption score and novelty score of all his/her publications in MAG.

(1) To assess scientific innovation, we rely on two primary metrics: disruption and novelty.

Disruption serves as a critical metric for evaluating innovative contributions to scientific research. Drawing on prior studies (Funk & Owen-Smith, 2017; Park et al., 2023; Wu et al., 2019), we quantify the disruption score as a measure of how a scientific paper introduces novelty by breaking away from existing paradigms. The disruption score is defined as:

$$Paper\ disruption = p_D - p_C = \frac{n_i - n_j}{n_i + n_j + n_k},$$

where n_i (the number of disruptive citations) represents the count of publications citing the focal paper (FP) without referencing its cited sources, n_j (the number of consolidating citations) denotes the count of publications citing FP and its references, and n_k represents the count of publications citing FP's references without citing FP itself. As depicted in Appendix Fig. A7, a lower disruption score indicates extensive citation of references by papers referencing the FP, aligning with established knowledge and consolidating existing paradigms. Conversely, higher disruption scores signify highly disruptive papers capable of inducing paradigm shifts.

To assess disruption at the author level, we compute the average disruption score across all papers authored by a scientist:

$$Avg\ disruption = \frac{\sum Paper\ disruption}{N},$$

where N represents the total number of publications by the scientist. Only publications with at least one reference and one citation are included in this calculation. This approach provides a single, aggregated disruption value for each scientist.

Novelty is conceptualized as the extent to which a paper employs atypical combinations of knowledge (Gates & Barabási, 2023; Lee et al., 2015; Uzzi et al., 2013). To measure this, we adopt the methodology of Uzzi et al. (2013), which utilizes the structure of citation networks to identify unexpected combinations of journal pairs in a paper's references. We perform ten Monte Carlo simulations (Shor et al., 2007) to create reshuffled citation networks that preserve the temporal and distributional properties of the original network. For each journal pair in the reference list of a focal paper, we calculate a standardized Z-score as follows:

$$Z\ score_{mn} = \frac{obs(pair_{mn}) - exp(pair_{mn})}{\sigma(pair_{mn})},$$

where $obs(pair_{mn})$ represents the observed frequency of the journal pair in the actual dataset, $exp(pair_{mn})$ denotes the mean, and $\sigma(pair_{mn})$ represents the standard deviation of the number of journal pairs obtained from 10 randomized simulations of the reshuffled network. The distribution of atypical knowledge combinations is denoted as a set:

$$Z\ score_{m,n} \mid m, n \in J$$

where J represents all journals in the reference list of the focal paper. To encapsulate the information contained within the distribution, we employ the 10th percentile of the $Z\ score_{m,n}$ set as a summary statistic, denoted as $Z\ score_{10pt}$, offering a quantifiable measure of the degree of atypical combination of knowledge exhibited by each paper.

$$Paper\ novelty = \begin{cases} -\ln(Z\ score_{10pt} + 1), if\ Z\ score_{10pt} > 0 \\ \ln(-Z\ score_{10pt} + 1), if\ Z\ score_{10pt} \le 0 \end{cases}.$$

We then aggregate novelty scores at the author level as:

$$Avg\ novelty = \frac{\sum Paper\ novelty}{N}.$$

(3) To further explore the relationship between delayed recognition and the innovative traits of scientists, we construct two author-level variables based on the characteristics of each publication's references. Following Wu et al. (2019), we define:

Reference age: The difference in publication years between the referenced paper and the focal paper.

Reference popularity: The number of citations received by the referenced paper.

These variables are aggregated at the author level to compute the average reference age and average reference popularity, which serve as proxies for the referencing behavior of scientists. These metrics provide insights into the potential mechanisms driving the association between delayed recognition and innovative characteristics.

(4) To enhance the robustness of our regression modeling framework and address potential sources of bias, we incorporate several control variables. These variables are carefully selected to account for inherent heterogeneity and ensure the reliability of our findings.

Disciplinary Heterogeneity. To address variability across scientific fields, we include 19 MAG primary fields as control variables. Each scientist is assigned a single primary field, determined based on their publication record. Specifically, the most frequently occurring field among their publications is designated as their home field. This approach captures nuanced differences among distinct scientific domains.

Temporal Trends. To account for temporal fluctuations and trends, we incorporate fixed effects for scientists' career start years, covering the period from 1970 to 2000. These fixed effects control for cohort-specific variations in scientific output and recognition over time.

Affiliation Effects. Affiliation fixed effects are included to mitigate heterogeneity associated with institutional affiliations. The MAG database provides disambiguated affiliation identifiers, which we use for this purpose. For scientists without an identifiable affiliation ID in MAG, we assign a placeholder value of 0.

Academic Status. We include several measures to account for scientists' academic status and career trajectory: (1) **Productivity**: The total number of publications listed in MAG. (2) **Total citations**: The cumulative number of citations received by the scientist's work, up to 2021. (3) **Career length**: The duration of a scientist's career, calculated as the difference between the year of their last publication and the year of their first publication.

Collaboration and Resource. To capture variations in collaboration patterns and resource utilization, we incorporate the following variables: (1) **Average team size**: The average size of research teams across the scientist's career. (2) **Average references**: The mean number of references cited per publication throughout the scientist's career. (3) **Average fundings**: The average number of funding acknowledgments from major agencies, specifically the National Institutes of Health (NIH) and the National Science Foundation (NSF), included in the scientist's authored papers.

By integrating these control variables, our analysis accounts for field-specific differences, temporal trends, institutional contexts, and individual academic profiles, thereby reducing potential confounding effects and strengthening the validity of our results. Table 1 presents the descriptive statistics for the variables included in our sample. The table reports the number of effective observations, mean values, standard deviations, as well as the minimum, 10th percentile, median, 90th percentile, and maximum values for each variable. Notably, many count-based variables, such as productivity, total citations, and average team size, exhibit significant skewness. To address this issue, these count variables are log-transformed in our regression models.

5.2. Female scientists are more likely to experience delayed recognition

Table 2 presents the results of OLS regression analyses exploring gender differences in delayed recognition among scientists, with controls for potential confounding factors such as career length, productivity, and total citations. The models examine both raw and rescaled metrics: the author beauty coefficient ($\boldsymbol{AB}$) and its rescaled version ($\boldsymbol{AB_f}$), as well as the author career awakening time ($\boldsymbol{A_{t\alpha}}$) and its rescaled form ($\boldsymbol{A_{t\alpha f}}$). Across all four models, the effect of gender is consistently positive and statistically significant ($\boldsymbol{p} < 0.001$), revealing that female scientists experience greater delayed recognition than their male counterparts.

On average, female scientists exhibit an $\boldsymbol{AB}$ 8.680 points higher than male scientists. Compared to the mean $\boldsymbol{AB}$ of 170.54, this

Table 1
Descriptive statistics.

Variables	Obs.	Avg	Std	Min	10 pct.	Median	90 pct.	Max
$\boldsymbol{AB}$	1678,906	170.54	802.88	−13.75	5.87	52.04	332.95	228,591.56
$\boldsymbol{t\alpha}$	1679,374	16.82	8.50	0.00	6.00	16.00	28.00	49.00
$\boldsymbol{AB_f}$	1678,906	1.00	3.72	−0.11	0.04	0.35	2.08	740.25
$\boldsymbol{t\alpha_f}$	1679,374	1.00	0.44	0.00	0.38	1.02	1.57	2.19
Productivity	1679,374	58.25	67.80	10.00	12.00	33.00	137.00	499.00
Total citations	1679,374	1790.01	4026.12	1.00	55.00	598.00	4337.00	416,771.00
Career length	1679,374	26.06	8.42	10.00	15.00	25.00	38.00	51.00
Gender (female)	1382,223	0.26	0.44	0.00	0.00	0.00	1.00	1.00
Avg #ref	1679,374	19.00	14.05	0.00	3.18	16.60	37.53	1043.83
Avg team size	1679,374	11.59	80.55	1.00	2.35	5.23	10.59	3021.45
Avg novelty	1600,911	−0.56	1.69	−10.37	−2.85	−0.38	1.48	4.90
Avg disruption	1622,826	0.00	0.04	−1.00	−0.01	0.00	0.02	0.99
Avg #funding	1679,374	0.16	0.53	0.00	0.00	0.00	0.41	39.79
Avg ref age	1637,024	10.11	4.16	−44.00	6.29	9.40	14.49	195.00
Avg ref pop.	1637,001	742.72	1065.68	1.00	134.16	487.66	1470.98	218,899.00

Table 2
Gender difference in delayed recognition of scientists (OLS regression).

Models	(1)	(2)	(3)	(4)
D.V.	AB	$A_{t\alpha}$	AB_f	$A_{t\alpha f}$
Female=1	8.680*** (1.544)	0.2968*** (0.0132)	0.0223** (0.0079)	0.0176*** (0.0008)
ln(Career length)	96.56*** (2.186)	11.13*** (0.0323)	0.4495*** (0.0097)	0.6018*** (0.0017)
ln(Productivity)	53.44*** (2.507)	0.6728*** (0.0130)	0.3072*** (0.0115)	0.0619*** (0.0007)
ln(Total citations)	20.38*** (1.730)	−0.7447*** (0.0094)	0.1440*** (0.0086)	−0.0578*** (0.0005)
ln(Avg #ref)	50.67*** (1.628)	1.010*** (0.0127)	0.2617*** (0.0088)	0.0727*** (0.0007)
ln(Avg team size)	275.8*** (8.369)	0.5456*** (0.0137)	1.260*** (0.0336)	0.0322*** (0.0008)
ln(Avg #funding)	10.14 (6.719)	−0.9789*** (0.0261)	−0.0520. (0.0302)	−0.0588*** (0.0016)
Field FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Affiliation FE	Yes	Yes	Yes	Yes
Obs.	1381,914	1382,223	1381,914	1382,223
$\mathbf{R^2}$	0.08572	0.36428	0.09397	0.19870

Note: robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

represents a 5.1 % increase (8.680 / 170.54 ≈ 0.051). Similarly, their awakening time ($\boldsymbol{A_{t\alpha}}$) is extended by 0.297 years—approximately 3.56 months—relative to male scientists. Against the mean $\boldsymbol{A_{t\alpha}}$ of 16.82 years, this equates to a 1.8 % increase (0.297 / 16.82 ≈ 0.018). These findings hold even after accounting for key career variables, underscoring a robust gender disparity in recognition timing.

Additional patterns emerge among the covariates. Higher total citation counts are linked to an increased $\boldsymbol{AB}$ but a reduced $\boldsymbol{A_{t\alpha}}$, suggesting that scientists with greater overall impact tend to achieve recognition earlier in their careers. Meanwhile, a higher average number of references per publication is associated with increases in both $\boldsymbol{AB}$ and $\boldsymbol{A_{t\alpha}}$, hinting at a connection between extensive citation practices and delayed acknowledgment.

5.3. Innovative scientists are more likely to experience delayed recognition

Table 3 reports OLS regression results assessing the link between research novelty—measured as the average novelty score across a scientist's publications—and delayed recognition, with controls for confounding factors. The analysis includes both raw ($\boldsymbol{AB}$, $\boldsymbol{A_{t\alpha}}$) and rescaled ($\boldsymbol{AB_f}$, $\boldsymbol{A_{t\alpha f}}$) metrics. In all four models, novelty exhibits a significant positive effect ($\boldsymbol{p} < 0.001$), indicating that scientists producing novel research, characterized by unconventional knowledge combinations, face greater delays in recognition.

A one-standard-deviation increase in average novelty (SD = 1.69) raises $\boldsymbol{AB}$ by 1.85 points (1.092 × 1.69), a 1 % increase relative to the mean $\boldsymbol{AB}$ of 170.54 (1.85 / 170.54 ≈ 0.01). For $\boldsymbol{A_{t\alpha}}$, the same increase delays awakening time by 0.05 years (0.0316 × 1.69), or about 0.2 % of the mean $\boldsymbol{A_{t\alpha}}$ of 16.82 years (0.05 / 16.82 ≈ 0.002). This suggests that scientists whose work consistently involves unconventional knowledge combinations face slower career-wide acknowledgment.

Table 4 examines the relationship between disruption—quantified as the average disruption score of a scientist's publications—and delayed recognition. Like novelty, disruption shows a consistent, significant positive association ($\boldsymbol{p} < 0.001$) across all four models. Scientists whose work disrupts established paradigms are more likely to experience delayed recognition before achieving broader acknowledgment.

A one-standard-deviation increase in average disruption (SD = 0.04) boosts $\boldsymbol{AB}$ by 7.3 points (182.7 × 0.04), a 4 % rise relative to the mean $\boldsymbol{AB}$ of 170.54 (7.3 / 170.54 ≈ 0.04). For $\boldsymbol{A_{t\alpha}}$, it extends awakening time by 0.16 years (3.998 × 0.04), roughly 1 % of the mean $\boldsymbol{A_{t\alpha}}$ of 16.82 years (0.16 / 16.82 ≈ 0.01). This reinforces that scientists whose body of work challenges established paradigms often wait longer for widespread career recognition.

Table 3
The relationship between novelty and delayed recognition of scientists.

Models	(1)	(2)	(3)	(4)
D.V.	AB	$A_{t\alpha}$	AB_f	$A_{t\alpha f}$
Avg novelty	1.092* (0.4501)	0.0316*** (0.0040)	0.0208*** (0.0020)	0.0030*** (0.0002)
ln(Career length)	110.8*** (2.134)	11.04*** (0.0273)	0.4710*** (0.0093)	0.5951*** (0.0015)
ln(Productivity)	60.68*** (2.304)	1.254*** (0.0117)	0.3558*** (0.0105)	0.0949*** (0.0007)
ln(Total citations)	15.91*** (1.641)	−1.273*** (0.0085)	0.1036*** (0.0081)	−0.0880*** (0.0005)
ln(Avg #ref)	75.18*** (1.568)	1.213*** (0.0125)	0.3615*** (0.0081)	0.0830*** (0.0007)
ln(Avg team size)	233.6*** (5.591)	0.3816*** (0.0106)	0.9963*** (0.0217)	0.0206*** (0.0006)
ln(Avg #funding)	63.04*** (6.973)	−0.3918*** (0.0244)	0.1505*** (0.0290)	−0.0226*** (0.0015)
Field FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Affiliation FE	Yes	Yes	Yes	Yes
Obs.	1600,615	1600,911	1600,615	1600,911
$\mathbf{R^2}$	0.08699	0.38142	0.09443	0.23040

Note: robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4
The relationship between disruption and delayed recognition of scientists.

Models	(1)	(2)	(3)	(4)
D.V.	AB	$A_{t\alpha}$	AB_f	$A_{t\alpha f}$
Avg disruption	182.7*** (6.410)	3.998*** (0.1796)	0.9102*** (0.0316)	0.1984*** (0.0097)
ln(Career length)	110.5*** (2.083)	11.02*** (0.0271)	0.4726*** (0.0090)	0.5944*** (0.0014)
ln(Productivity)	60.06*** (2.244)	1.214*** (0.0116)	0.3496*** (0.0102)	0.0922*** (0.0007)
ln(Total citations)	16.76*** (1.589)	−1.226*** (0.0084)	0.1105*** (0.0078)	−0.0850*** (0.0005)
ln(Avg #ref)	71.60*** (1.352)	1.186*** (0.0120)	0.3597*** (0.0072)	0.0817*** (0.0007)
ln(Avg team size)	231.3*** (5.526)	0.3575*** (0.0105)	0.9836*** (0.0214)	0.0188*** (0.0006)
ln(Avg #funding)	65.84*** (6.898)	−0.3854*** (0.0243)	0.1646*** (0.0286)	−0.0217*** (0.0015)
Field FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Affiliation FE	Yes	Yes	Yes	Yes
Obs.	1622,456	1622,826	1622,456	1622,826
R^2	0.08664	0.38039	0.09415	0.22805

Note: robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Tables 5 and 6 provide additional context based on scientist-level reference characteristics. Table 5 reveals a positive link between average reference age—computed across a scientist's entire publication history—and delayed recognition. Scientists whose careers rely more heavily on older knowledge sources tend to face longer delays, possibly because their work requires time to resonate within modern scientific contexts. Conversely, Table 6 shows a negative association between average reference popularity—also aggregated at the scientist level—and delayed recognition. Scientists whose citation patterns favor less-cited references over their careers are more likely to experience delays, likely due to the niche or unconventional nature of their knowledge base.

6. Scientists in small groups experience more delayed recognition

In this section, we explore why innovative scientists often face delayed recognition, focusing on the role of academic group size. Previous research by Wu et al. (2019) showed that large teams tend to build on existing science and technology, while small teams are more likely to produce disruptive, groundbreaking work. Additionally, Xing et al. (2025) found that mentees trained in larger groups outperform those from smaller groups in academic achievements—provided they stay in academia after graduation—but they also noted that mentees from larger groups have a lower survival rate in academic careers. Building on these insights, we investigate whether scientists trained in small groups experience greater delayed recognition compared to those in large groups, using academic group size as our key variable.

Since we couldn't get the whole mentor-mentee data from the Academic Family Tree used by Xing et al. (2025), we instead relied on dynamic citation and publication data from MAG. Specifically, we constructed early-career profiles for each scientist based on their first five years in academia—a period typically corresponding to Ph.D. or postdoctoral stages. For each scientist, we calculated their average team size during this time, using publication co-authorship as a proxy for group size. To define "large" and "small" groups, we ranked scientists within each cohort (based on career start year) and field (using MAG's level-0 categories). The top 20 % of average team sizes in each cohort and field were classified as "large groups," while the bottom 20 % were classified as "small groups."

To ensure fair comparisons between scientists from large and small groups, we used Coarsened Exact Matching (CEM) (Iacus et al., 2012). CEM improves comparability by matching scientists with similar characteristics. The process involves three steps: (1) grouping key variables (e.g., gender, field) into broader categories for matching; (2) dividing scientists into strata with identical coarsened values; and (3) removing strata that lack both a large-group and small-group scientist. We matched scientists one-to-one based on

Table 5
The relationship between knowledge age and delayed recognition of scientists.

Models	(1)	(2)	(3)	(4)
D.V.	AB	$A_{t\alpha}$	AB_f	$A_{t\alpha f}$
Avg ref age	35.58*** (2.013)	3.318*** (0.0232)	0.1053*** (0.0088)	0.1793*** (0.0013)
ln(Career length)	104.4*** (2.027)	10.32*** (0.0275)	0.4580*** (0.0088)	0.5562*** (0.0015)
ln(Productivity)	58.58*** (2.213)	0.8617*** (0.0116)	0.3415*** (0.0101)	0.0724*** (0.0007)
ln(Total citations)	19.14*** (1.576)	−0.8056*** (0.0086)	0.1207*** (0.0077)	−0.0616*** (0.0005)
ln(Avg #ref)	63.31*** (1.378)	0.8762*** (0.0118)	0.3262*** (0.0073)	0.0654*** (0.0007)
ln(Avg team size)	233.0*** (5.623)	0.6155*** (0.0107)	0.9859*** (0.0218)	0.0328*** (0.0006)
ln(Avg #funding)	71.12*** (6.883)	−0.3380*** (0.0241)	0.1823*** (0.0285)	−0.0199*** (0.0014)
Field FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Affiliation FE	Yes	Yes	Yes	Yes
Obs.	1636,072	1636,466	1636,072	1636,466
R^2	0.08646	0.38509	0.09393	0.23439

Note: robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6
The relationship between knowledge popularity and delayed recognition of scientists.

Models	(1)	(2)	(3)	(4)
D.V.	AB	$A_{t\alpha}$	AB_f	$A_{t\alpha f}$
Avg ref pop.	−1.834*** (0.4187)	−0.1372*** (0.0072)	−0.0143*** (0.0021)	−0.0068*** (0.0004)
ln(Career length)	112.7*** (2.051)	11.10*** (0.0272)	0.4827*** (0.0089)	0.5982*** (0.0014)
ln(Productivity)	60.30*** (2.181)	1.018*** (0.0117)	0.3464*** (0.0099)	0.0809*** (0.0007)
ln(Total citations)	16.73*** (1.529)	−1.029*** (0.0086)	0.1144*** (0.0075)	−0.0738*** (0.0005)
ln(Avg #ref)	66.37*** (1.366)	1.162*** (0.0120)	0.3383*** (0.0073)	0.0806*** (0.0007)
ln(Avg team size)	229.6*** (5.489)	0.3023*** (0.0106)	0.9759*** (0.0213)	0.0158*** (0.0006)
ln(Avg #funding)	69.49*** (6.869)	−0.5007*** (0.0244)	0.1776*** (0.0285)	−0.0287*** (0.0015)
Field FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Affiliation FE	Yes	Yes	Yes	Yes
Obs.	1636,606	1637,001	1636,606	1637,001
$\mathbf{R^2}$	0.08630	0.37241	0.09387	0.22069

Note: robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

features like gender, primary field, career start year, average reference counts, citation counts, disruption scores (all from the first five years of publications), and affiliation rank. From our total sample of 1.68 million scientists, we successfully matched 2466 large-group scientists with 2466 small-group scientists. An examination of the characteristics of the two groups revealed that they were statistically indistinguishable across all measured dimensions (Appendix A2).

Using these matched groups, we conducted two main analyses. First, we performed a Kaplan-Meier survival analysis to examine how long scientists remained in academia. Dropout is defined as the year a scientist ceases publishing in MAG. As shown in Fig. 3a, scientists from large groups exhibited a steeper drop-off, indicating they were more likely to leave academia early compared to those from small groups. Second, we compared delayed recognition metrics—specifically the author beauty coefficient (***AB***) and author career awakening time ($\boldsymbol{A_{t\alpha}}$)—between these two groups. Results in Figs. 3b–d show that small-group scientists had a significantly higher ***AB*** (60.2 vs. 45.1, Welch's t-test $p < 0.001$) and a longer $\boldsymbol{A_{t\alpha}}$ (16.2 vs. 11.1 years, Welch's t-test $p < 0.001$). This suggests that their recognition is delayed longer and more intensely.

We also examined long-term success metrics, such as the h-index and total citations. Figs. 3e–g reveal that small-group scientists had a lower h-index (3.8 vs. 3.4, Welch's t-test $p < 0.001$) and fewer total citations (95.4 vs. 149.0, Welch's t-test $p < 0.001$) compared to large-group scientists. These findings align with Xing et al. (2025), showing that among scientists who survive at least 8 years in academia (per our sample criteria), those from large groups tend to achieve greater overall success. However, our key finding is that small-group scientists, despite potentially being more disruptive, experience significantly higher levels of delayed recognition. This sheds light on the connection between innovation and delayed acknowledgment at the individual scientist level.

7. Discussion

The phenomenon of delayed recognition has long been recognized as a critical feature of scientific progress, yet its exploration has largely been confined to the level of individual publications. This study advances the field by reframing delayed recognition as a career-level attribute, introducing a novel framework that quantifies its dynamics through the author beauty coefficient (***AB***) and the author career awakening time ($\boldsymbol{A_{t\alpha}}$). By analyzing the citation trajectories of 1.679 million scientists from MAG, we uncover patterns that diverge significantly from paper-level measures, offering a more comprehensive lens on how scientific impact unfolds over time. Our findings not only validate the utility of this approach but also illuminate the demographic and research factors that exacerbate delays, with far-reaching implications for equity, innovation, and science policy.

A central contribution of this work is the demonstration that scientist-level delayed recognition captures distinct dimensions from paper-level analyses. The lack of correlation between ***AB*** and averaged paper beauty coefficients underscores that career-wide recognition is not a simple aggregate of individual publication trajectories. For instance, the contrasting cases of John C. Mather and H. David Politzer highlight how scientists with similar paper-level metrics can experience vastly different career recognition timelines. This divergence suggests that factors beyond publication output—such as systemic biases, research context, or collaboration networks—play a pivotal role in shaping when and how scientists achieve acknowledgment. By extending the analytical scope to the career level, our framework provides a more nuanced understanding of scientific impact, aligning with calls to move beyond reductionist metrics in evaluating research contributions (Hicks et al., 2015).

Our regression analyses reveal that female scientists consistently face greater delayed recognition, with an ***AB*** increase of 5.1 % and an $\boldsymbol{A_{t\alpha}}$ extension of 1.8 % compared to their male counterparts. This gender disparity persists even after controlling for career length, productivity, and total citations, pointing to structural inequities in the scientific ecosystem. These findings resonate with prior evidence of gender biases in citation practices and career advancement (Ross et al., 2022; Yang, Ding et al., 2024; Yang et al., 2022), but our career-level perspective adds a temporal dimension: women's contributions may be systematically undervalued early on, only gaining traction later. Similarly, scientists pursuing novel or disruptive research—marked by unconventional knowledge combinations or paradigm-shifting outputs—experience heightened delays, with disruption showing a stronger effect (4 % ***AB*** increase) than novelty (1 % increase). This aligns with the notion that transformative ideas often face initial resistance or require time to permeate established frameworks (Wu et al., 2019; Yang, Zhao et al., 2024).

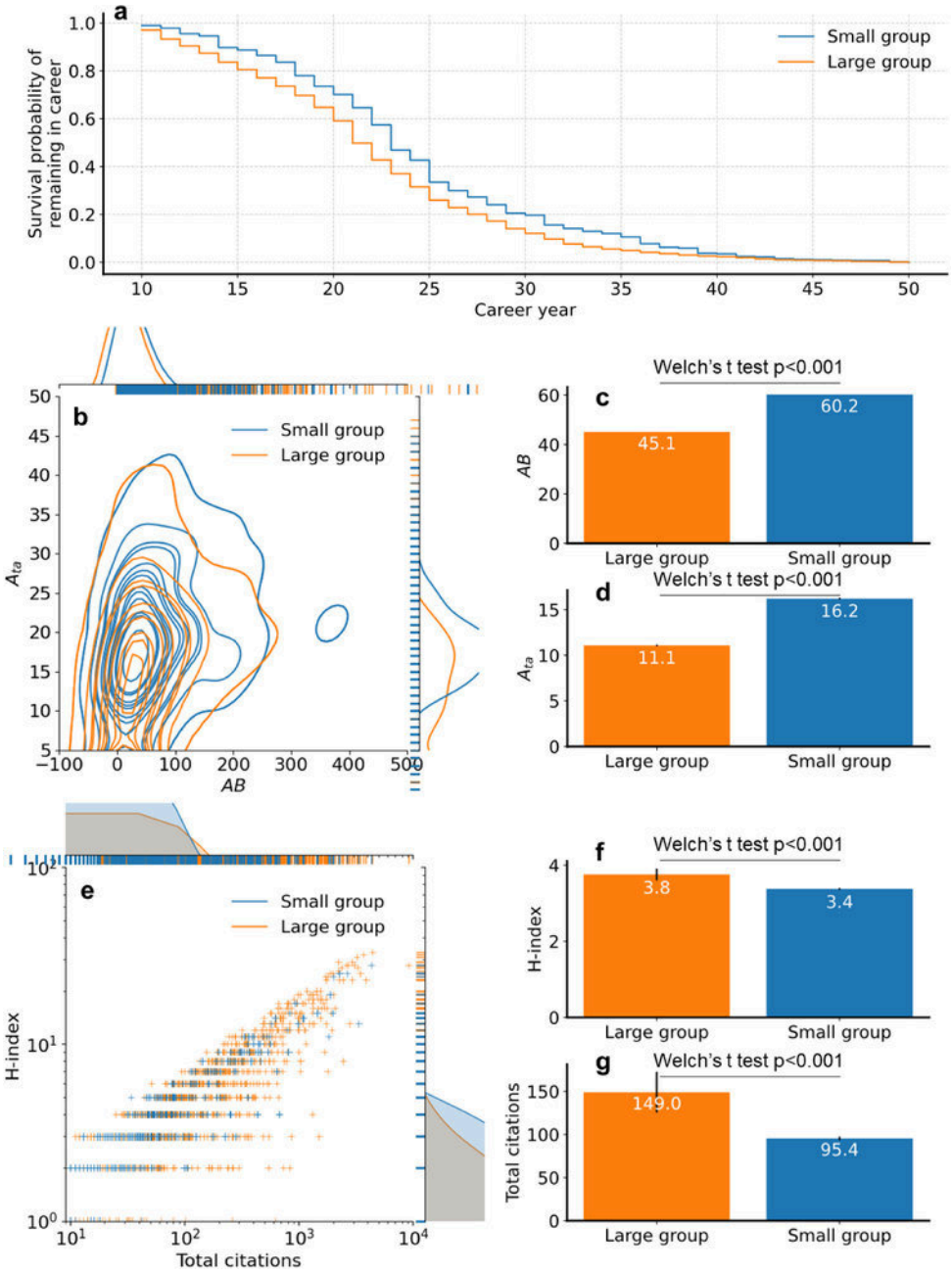


Fig. 3. Career Patterns of Scientists from Large vs. Small Groups. This figure compares career trajectories of scientists from large and small groups, based on two comparable cohorts created using Coarsened Exact Matching (CEM). (a) Kaplan-Meier survival analysis showing the dropout rates of scientists from large vs. small groups, measuring how long they remain active in academia. Dropout is defined as the year a scientist ceases publishing in MAG. (b) Kernel Density Estimation (KDE) plot illustrating the distribution of the author beauty coefficient (***AB***) and author career awakening time ($\boldsymbol{A}_{t\alpha}$) for large vs. small group scientists, with marginal distributions and rug plots included. (c–d) Bar or box plot comparisons of the author beauty coefficient (c) and author career awakening time (d) between large and small group scientists, with Welch's *t*-test indicating significant differences ($p < 0.001$). (e) Scatter plot of h-index versus total citations for large vs. small group scientists, with marginal distributions and rug plots shown. (f–g) Bar or box plot comparisons of h-index (f) and total citations (g) between large and small group scientists, with Welch's *t*-test confirming significant differences ($p < 0.001$).

The role of group size further enriches this narrative. Through Coarsened Exact Matching (CEM), we find that scientists from smaller academic groups exhibit higher $\boldsymbol{AB}$ (60.2 vs. 45.1) and longer $\boldsymbol{A_{t\alpha}}$ (16.2 vs. 11.1 years) than their large-group peers, despite greater persistence in academia. This paradox—higher survival yet delayed recognition—suggests that small teams, often linked to disruptive innovation (Wu et al., 2019), may lack the visibility or resources of larger groups, deferring their impact. Conversely, large-group scientists, who tend to build on existing science, achieve earlier recognition and higher traditional success metrics (e.g., h-index, total citations), consistent with Xing et al. (2025). These findings highlight a trade-off between innovation and immediacy, raising questions about how academic structures reward different modes of scientific production.

Our framework for quantifying delayed recognition at the scientist level captures two key drivers distinct from paper-level analyses. First, delayed recognition may stem from published work that is initially overlooked by the scientific community, similar to the "Sleeping Beauty" phenomenon. Second, unique to the scientist level, it may arise from delayed productivity, where scientists—often "late bloomers"—publish their most impactful work later in their careers, as seen in John C. Mather's trajectory. Our metrics aggregate career-level citation trajectories to reflect both mechanisms. However, these drivers may not fully account for all instances of delayed recognition, as other factors, such as collaboration networks or institutional visibility, could also play a role. While a detailed analysis to disentangle these contributions is beyond this study's scope, it represents a promising avenue for future research to further elucidate career-level recognition dynamics.

While our study leverages a robust dataset and rigorous methods, it is not without limitations. The reliance on MAG introduces potential biases from name disambiguation errors, though its high precision mitigates this concern. Gender inference via first names, while statistically validated, may misclassify some individuals, particularly in culturally diverse contexts. Additionally, our focus on scientists with at least 8 years of activity and 10–500 publications excludes early-career researchers and hyper-prolific authors, potentially skewing the sample toward established careers. Besides, co-authorship as a proxy for group size simplifies complex mentorship and collaboration dynamics, which could be refined with direct relational data in future work. Finally, we use citation counts as a proxy for scientific recognition. While citations are a commonly accepted measure of impact, they do not encompass other forms of recognition, such as patents, media attention, or societal influence, which could provide a more holistic view of a scientist's contributions.

Looking ahead, several avenues warrant exploration. Integrating mentorship data could clarify how training environments shape recognition trajectories, building on our group-size findings. Longitudinal studies tracking early-career scientists could test whether delayed recognition patterns emerge earlier than our 8-year threshold suggests. Moreover, applying this framework across cultural and institutional contexts could reveal how global science systems influence recognition delays. Ultimately, by reframing delayed recognition as a career-level phenomenon, this study not only deepens our theoretical understanding of scientific impact but also lays the groundwork for a more equitable and innovative scientific enterprise.

CRediT authorship contribution statement

Alex J. Yang: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Yiqin Zhang:** Writing – original draft, Validation, Supervision. **Zuorong Wang:** Validation, Resources, Methodology. **Hao Wang:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis. **Sanhong Deng:** Writing – review & editing, Writing – original draft, Resources, Methodology, Conceptualization.

Conflict of Interest

We declare no competing interest relevant to this article.

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Appendix

Appendix A1. Rescaling metrics

Citations and innovation indices at the paper level exhibit significant heterogeneity across disciplines and time periods (Chu & Evans, 2021; Radicchi & Castellano, 2011; Radicchi et al., 2008; Yang, Gong et al., 2024), and this variability is similarly reflected in the delayed recognition metrics at the scientist level. In our analysis, we categorize scientists by their career start year to define temporal cohorts and by their MAG primary field (spanning 19 distinct disciplines) to represent disciplinary categories. Notably, our

dataset includes only scientists with a minimum career length of eight years, ensuring reliable comparisons across different cohorts (Figs. A6 and A8).

Fig. A1 illustrates the average values of the delayed recognition metrics—namely, the author beauty coefficient (***AB***) and the author career awakening time ($\boldsymbol{A_{t\alpha}}$)—for scientists within each field as a function of their career start year. The results reveal substantial variability in ***AB*** and $\boldsymbol{A_{t\alpha}}$ both across disciplines and over time. Specifically, the average ***AB*** for scientists from the same career start year in one field can be as much as three times higher than that in another field. Additionally, both ***AB*** and $\boldsymbol{A_{t\alpha}}$ tend to decline with more recent career start years, though this trend exhibits limited fluctuations. To account for potential biases introduced by variations in citation counts and career lengths, we normalize ***AB*** by each author's total career citation count and normalize $\boldsymbol{A_{t\alpha}}$ by career length. The observed trends and disparities persist even after normalization, underscoring the robustness of these findings (Fig. A1c-d). In the field of Medicine, for instance, for scientists whose careers began in 1971, the average ***AB*** is approximately 346, and $\boldsymbol{A_{t\alpha}}$ is around 23 years. In contrast, for those with a career start year of 1999, the average ***AB*** and $\boldsymbol{A_{t\alpha}}$ drop to approximately 107 and 12 years, respectively. These findings highlight significant differences in delayed recognition metrics across fields and career cohorts. Importantly, these disparities persist even after controlling for total citation counts and career length, posing critical challenges for cross-cohort and cross-disciplinary comparisons of delayed recognition metrics.

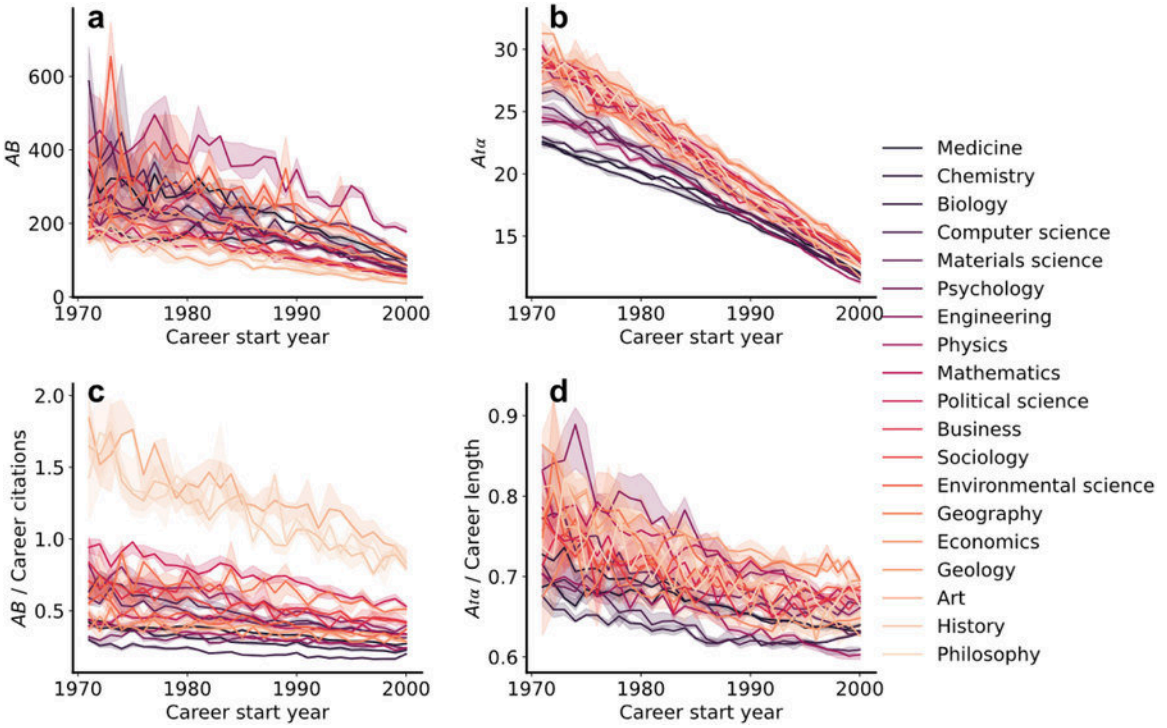


Fig. A1. Trends in average delayed recognition metrics of scientists across years and disciplines. (**a**) The average author beauty coefficient (***AB***) of scientists categorized by career start year from 1970 to 2020. Each colored line represents a distinct field, with shaded areas indicating 95 % bootstrap confidence intervals. (**b**) The average author career awakening time ($\boldsymbol{A_{t\alpha}}$) of scientists as a function of career start year across fields. (**c**) Normalized ***AB*** values (scaled by total career citations) plotted over career start year and across fields. (**d**) Normalized $\boldsymbol{A_{t\alpha}}$ values (scaled by career length) displayed over career start year and across fields.

To address the issue highlighted in the previous section, we employ a relative method for normalization. This approach is appropriate because the author-level delayed recognition metrics, such as the author beauty coefficient (***AB***) and author career awakening time ($\boldsymbol{A_{t\alpha}}$), follow power law distributions within each category. These scale-free distributions are well-suited to rescaling through a relative citation method. We define the rescaled author beauty coefficient ($\boldsymbol{AB_f}$) as:

$$\boldsymbol{AB_f} = \frac{AB}{\widetilde{AB}},$$

where $\widetilde{AB}$ represents the mean value of ***AB*** within the relevant category (field and career start year). Similarly, we define the rescaled author career awakening time ($\boldsymbol{A_{t\alpha f}}$) as:

$$\boldsymbol{A}_{t\alpha f} = \frac{A_{t\alpha}}{\widetilde{A_{t\alpha}}},$$

where $\widetilde{A_{t\alpha}}$ represents the mean value of $\boldsymbol{A}_{t\alpha}$ within the relevant category. These rescaled metrics quantify the delayed recognition of a scientist in comparison to other scientists within the same field and career start year. A value of $\boldsymbol{AB}_f > 1$ or $\boldsymbol{A}_{t\alpha f} > 1$ indicates that a scientist's delayed recognition is above the average for that category. By definition, the average value of both $\boldsymbol{AB}_f$ and $\boldsymbol{A}_{t\alpha f}$ is 1 for any given field or career start year.

However, this normalization alone is insufficient to provide an unbiased and useful indicator. To ensure a fair comparison across fields and career start years, it is necessary that the distributions of these rescaled metrics are consistent, meaning the probability of obtaining any specific value of $\boldsymbol{AB}_f$ or $\boldsymbol{A}_{t\alpha f}$ is the same across all fields and career cohorts.

Figs. A2 and A3 illustrate the distributions of both the raw and rescaled delayed recognition metrics—$\boldsymbol{AB}$ and $\boldsymbol{A}_{t\alpha}$, as well as $\boldsymbol{AB}_f$ and $\boldsymbol{A}_{t\alpha f}$ —for each category. A comparison of the raw and rescaled values demonstrates that the normalization procedure effectively brings all distributions into alignment, allowing for a fair comparison of delayed recognition metrics across different fields and years. After rescaling, the distributions of $\boldsymbol{AB}_f$ and $\boldsymbol{A}_{t\alpha f}$ appear to be universal across all categories and closely resemble lognormal distributions. Each distribution of the rescaled metrics can be fitted to a lognormal curve, as described by the following equations:

$$F(\boldsymbol{AB}_f) = \frac{1}{\sigma AB_f\sqrt{2\pi}} e^{-\frac{-\left(\log\left(AB_f\right)-\mu\right)^2}{2\sigma^2}},$$

or

$$F(\boldsymbol{A}_{t\alpha f}) = \frac{1}{\sigma A_{t\alpha f}\sqrt{2\pi}} e^{-\frac{-\left(\log\left(A_{t\alpha f}\right)-\mu\right)^2}{2\sigma^2}},$$

where the relation $\sigma^2 = -2\mu$, because the expected value of the variable $\boldsymbol{AB}_f$ and $\boldsymbol{A}_{t\alpha f}$ is 1, reduces the number of fitting parameters to 1. The relative rescaling method effectively normalizes delayed recognition metrics across disciplines and time periods, yielding distributions that are comparable and follow a lognormal pattern. This approach facilitates unbiased, cross-field and cross-cohort comparisons of delayed recognition in scientific careers.

The universal scaling observed in the rescaled metrics provides a robust foundation for comparing scientists across different disciplines. To illustrate this more explicitly, we ranked scientists from various fields based on both the raw and rescaled metrics. A quantitative evaluation of the improvements afforded by rescaled metrics over raw metrics can be achieved by examining the rank distribution across fields and career start years. Specifically, we rank scientists within each category either by their raw metrics or by the rescaled indicators and then assess the results. Our analysis reveals that rankings based on raw metrics exhibit considerable heterogeneity across fields and periods, whereas rankings based on rescaled metrics demonstrate uniformity, with the same average value across all sets. Fig. A4 highlights the disparities observed when ranking scientists by the raw author career awakening time ($\boldsymbol{A}_{t\alpha}$), which shows significant variability among fields and career start years. These disparities are substantially mitigated when using the rescaled author career awakening time ($\boldsymbol{A}_{t\alpha f}$) metric. To quantify this improvement, we consider the expected value of the bin height, which under the assumption of unbiased rankings should be 0.5, with a standard deviation given by: $\sigma = \sqrt{\frac{0.5(1-0.5)}{N_c}\sum\frac{1}{N_i}}$, where N_c is the number of categories, and N_i is the number of articles in the *ith* category. Rankings based on the rescaled metric align closely with the hypothesis of unbiased distributions, whereas rankings derived from the raw values provide strong evidence of bias.

Appendix Fig. A5 further corroborates these findings by presenting results for the raw author beauty coefficient ($\boldsymbol{AB}$) and the rescaled author beauty coefficient ($\boldsymbol{AB}_f$) across various fields and career start years. Similar patterns are observed, with the rescaled metrics achieving significant reductions in variability and enabling fair comparisons across disciplines and cohorts. Overall, the rescaled metrics facilitate unbiased rankings and consistent cross-field comparisons, effectively addressing the heterogeneity inherent in raw metric distributions.

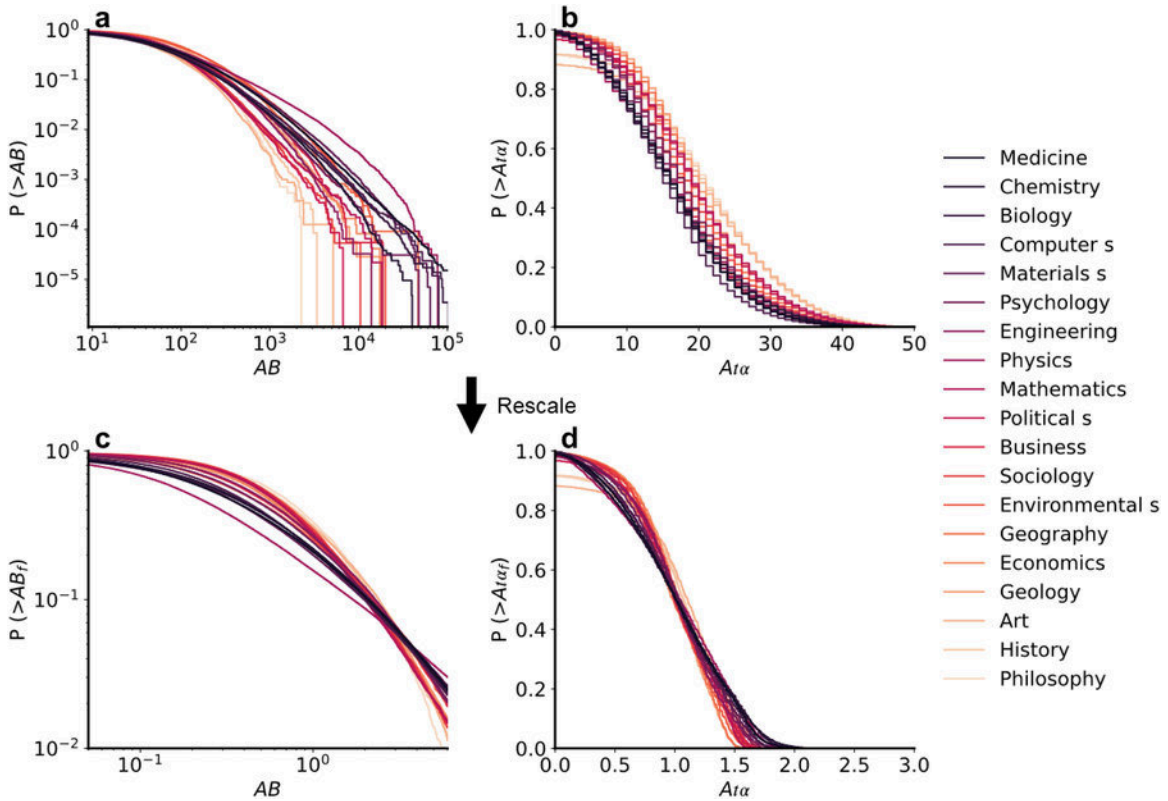


Fig. A2. Cumulative distributions of raw and rescaled delayed recognition metrics for scientists across 19 MAG primary fields. (**a**) Distribution of the author beauty coefficient (***AB***), showing a power law pattern. (**b**) Distribution of the author career awakening time ($A_{t\alpha}$), also following a power law distribution. (**c**) Distribution of the rescaled author beauty coefficient (AB_f), aligning with a single lognormal curve. (**d**) Distribution of the rescaled author career awakening time ($A_{t\alpha f}$), similarly conforming to a single lognormal curve. These results highlight the transition from heterogeneous, scale-free raw distributions to consistent, normalized distributions through rescaling.

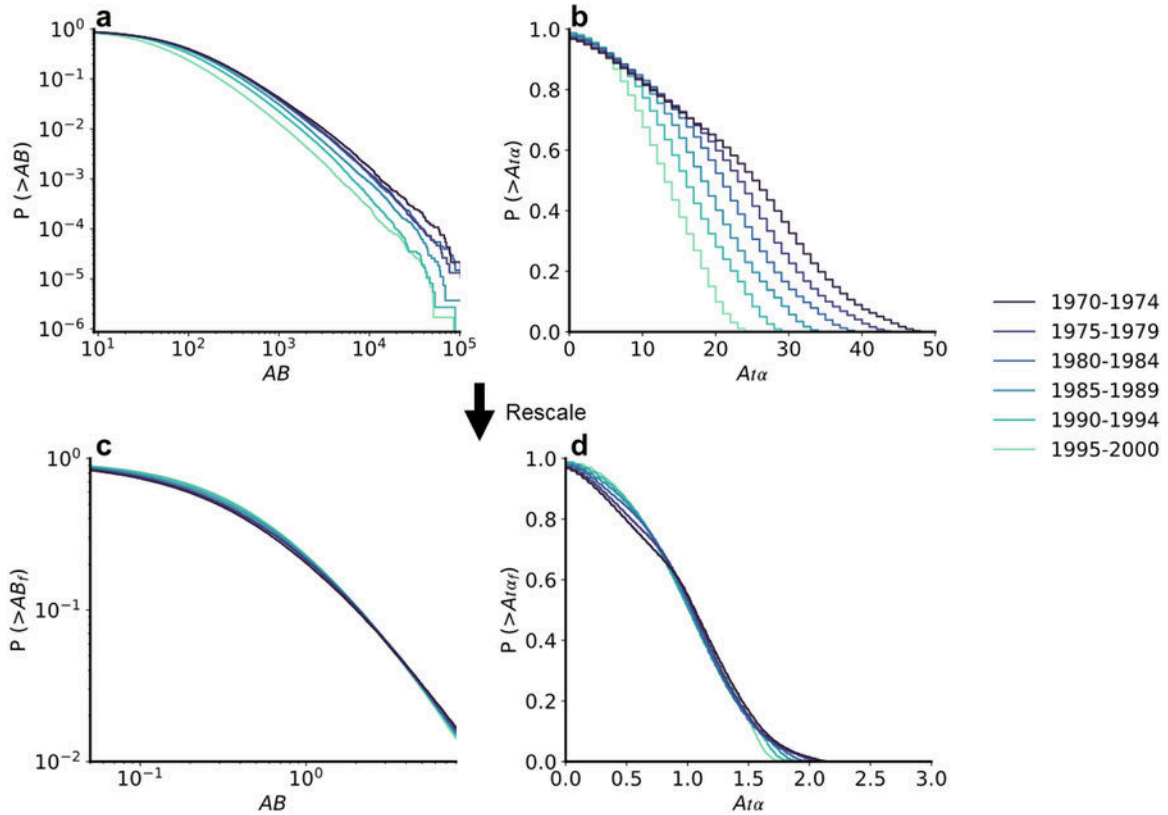


Fig. A3. Cumulative distributions of raw and rescaled delayed recognition metrics for scientists across different career start years. (**a**) Distribution of the author beauty coefficient (***AB***), showing a power law pattern. (**b**) Distribution of the author career awakening time ($\boldsymbol{A_{t\alpha}}$), also following a power law distribution. (**c**) Distribution of the rescaled author beauty coefficient ($\boldsymbol{AB_f}$), aligning with a single lognormal curve. (**d**) Distribution of the rescaled author career awakening time ($\boldsymbol{A_{t\alpha f}}$), similarly conforming to a single lognormal curve. These results highlight the transition from heterogeneous, scale-free raw distributions to consistent, normalized distributions through rescaling.

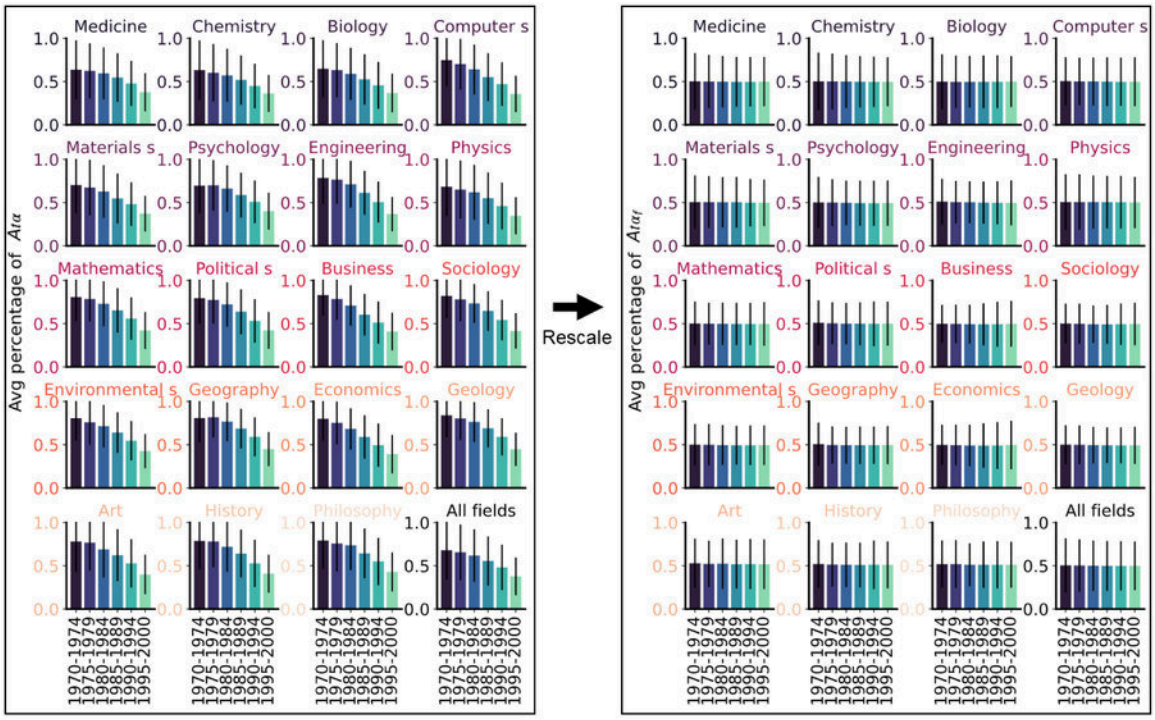


Fig. A4. Histograms showing the average percentage of scientists in the global ranking based on raw metric (author career awakening time $A_{t\alpha}$) in the left column and rescaled metric (the rescaled author career awakening time $A_{t\alpha f}$) in the right column. Each subset corresponds to scientists grouped by field, with bar colors representing different career start years. Error bars indicate the standard deviation for each category.

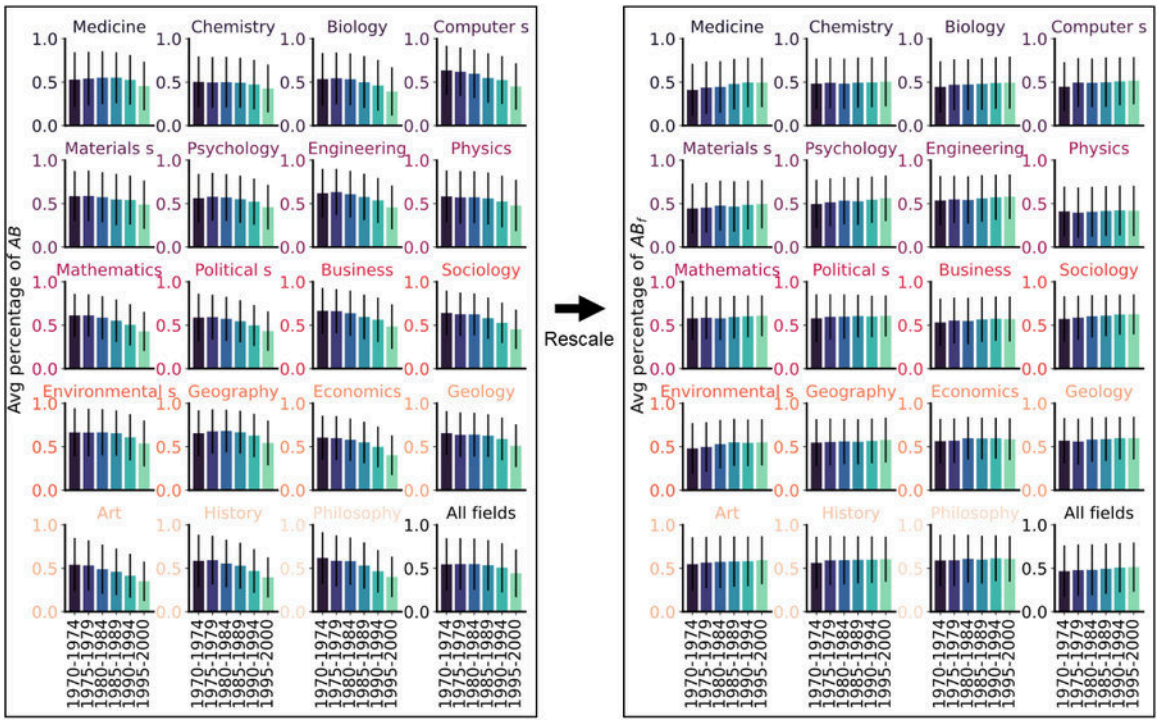


Fig. A5. Histograms showing the average percentage of scientists in the global ranking based on raw metric (author beauty coefficient AB) in the left column and rescaled metric (rescaled author beauty coefficient AB_f) in the right column. Each subset corresponds to scientists grouped by field, with bar colors representing different career start years. Error bars indicate the standard deviation for each category.

Appendix A2. CEM results

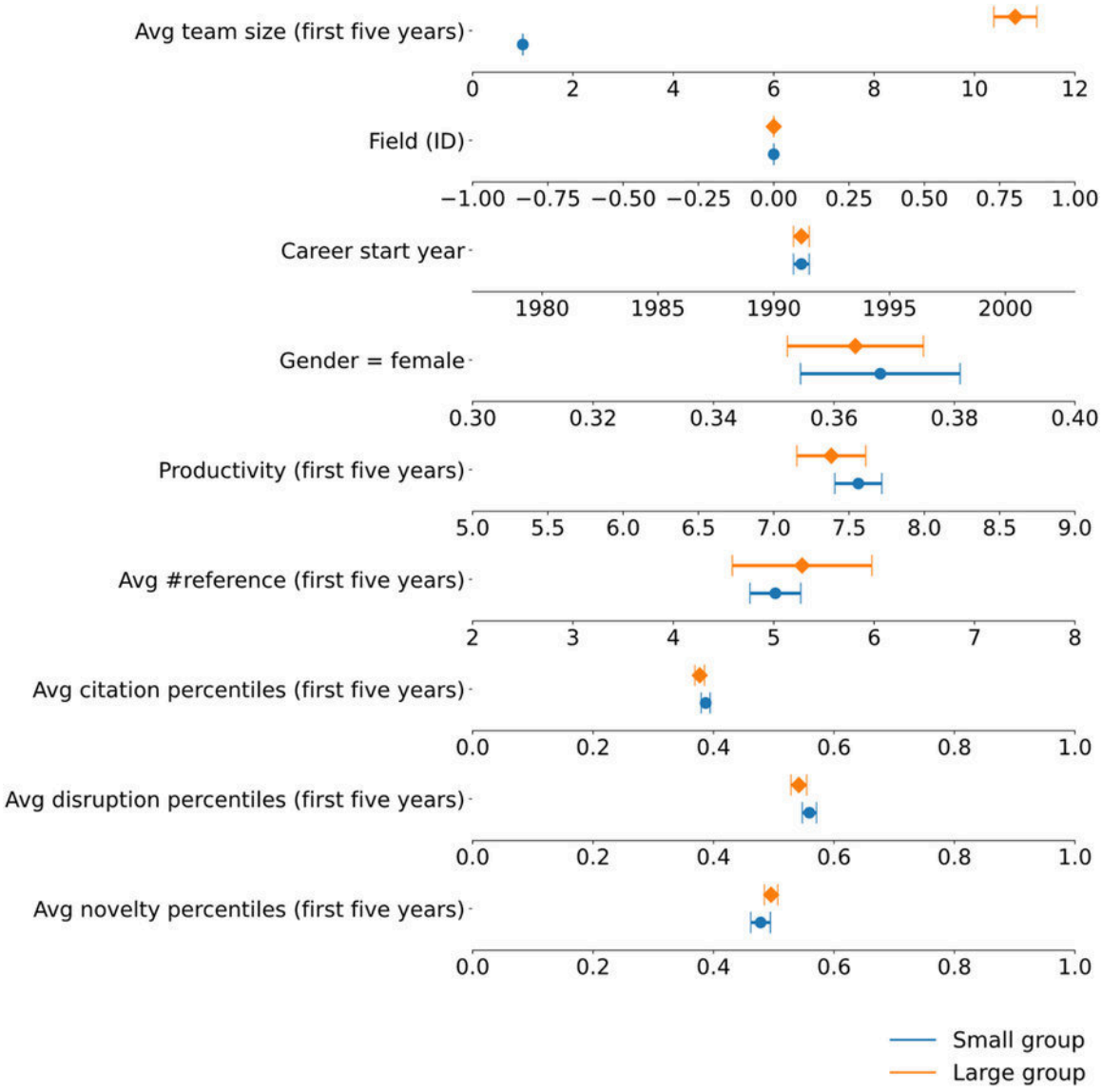


Fig. A6. Post-CEM feature comparisons between scientists in small group and large group. They were statistically indistinguishable across all measured dimensions.

Appendix A3. Other figures

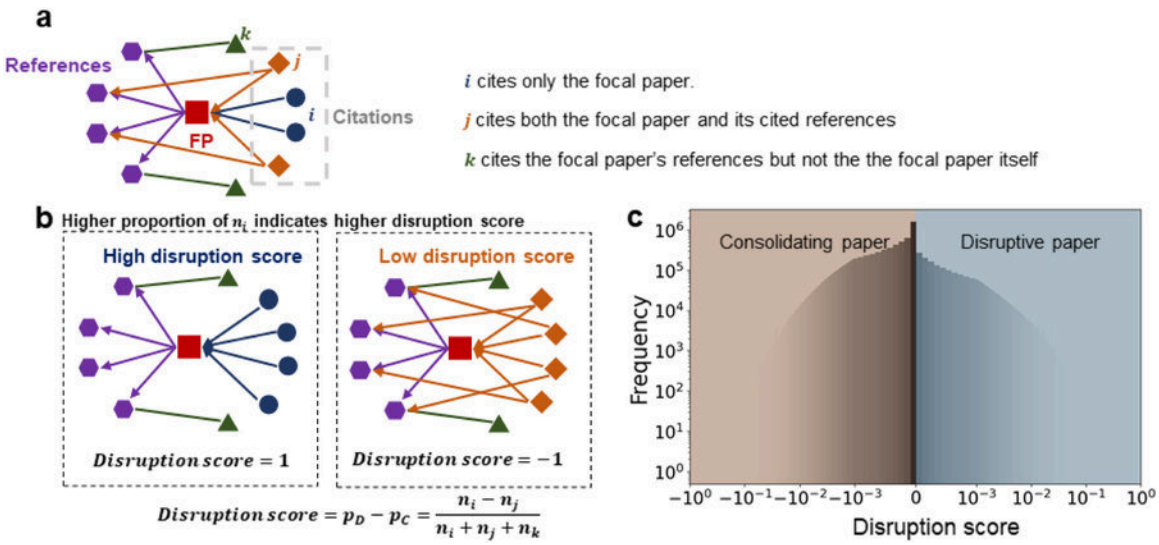


Fig. A7. Quantifying disruptiveness. (a-b) a simplified depiction of disruption dynamics. Subsequent works may cite the focal paper alone (*i*, depicted in blue), both the focal paper and its references (*j*, depicted in orange), or solely its references (*k*, depicted in black). Disruption score for the focal paper is defined as the discrepancy between the proportions of type *i* and *j* papers. (**c**) The distribution of disruption score across all MAG articles.

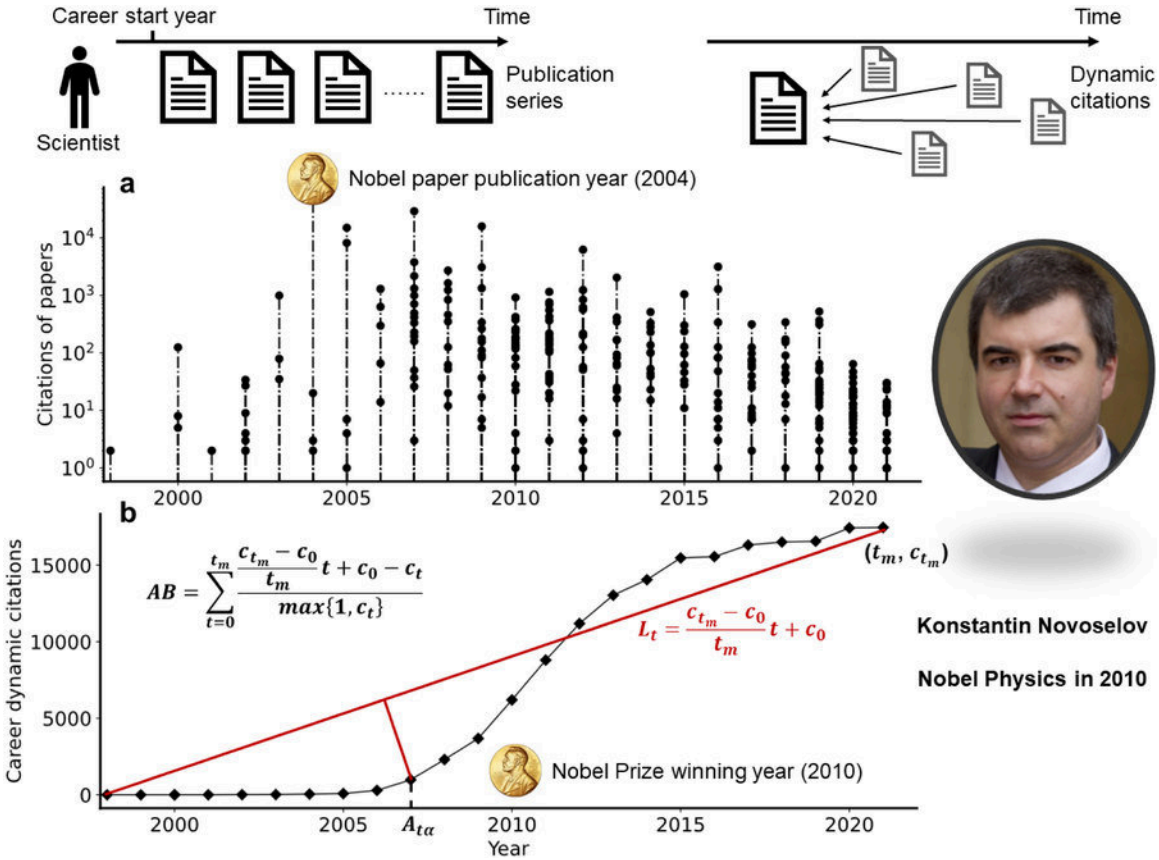


Fig. A8. Framework for Quantifying Delayed Recognition in Scientists. This figure illustrates the methodology for constructing and analyzing the career-level dynamic citation trajectory of individual scientists, exemplified by Nobel laureate Konstantin Novoselov. (**a**) The citation trajectories of all publications authored by a single scientist are aggregated to create a comprehensive representation of yearly citation counts over the

scientist's career. (**b**) The delayed recognition framework is depicted, including the derivation of the author beauty coefficient (***AB***) and the author career awakening time ($A_{t\alpha}$). These metrics are calculated based on the career-level citation trajectory. For Konstantin Novoselov, the analysis indicates that the author career awakening time ($A_{t\alpha} = 9$) occurred three years after the publication of his Nobel-winning work (2004) and three years prior to receiving the Nobel Prize (2010).

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