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Unveiling the dynamics of team age structure and its impact on scientific innovation

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Abstract
In the dynamic landscape of contemporary scientific research characterized by increasing collaboration, this study, leveraging a comprehensive dataset spanning six decades and encompassing 16 diverse fields with 30 million journal papers, conducts the first large-scale analysis of age structure within scientific teams. Our findings illuminate a consistent upward trajectory in the average team age over time, coupled with a concurrent decline in team age diversity. Examining their intricate relationships with scientific impact, we unveil intriguing inverted-U associations between team age, team age diversity, and scientific impact. This underscores the optimal performance of moderately aged and diverse teams in terms of team impact. Additionally, our research uncovers a U-shaped relationship between team age, team age diversity, and scientific disruption, emphasizing the disruptive potential of extreme team age patterns. Importantly, these discerned patterns hold robustly across various fields and team sizes, offering valuable insights for strategically composing scientific teams and enhancing their productivity in the collaborative landscape of scientific research.

Keywords Science of science · Team age · Team age diversity · Scientific impact · Disruption

Introduction

The landscape of contemporary science in the past century has undergone a profound transformation characterized by an escalating reliance on collaborative efforts (Azoulay et al., 2018; Larivière et al., 2015; Wang & Barabási, 2021; Yang et al., 2021). This paradigm

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shift has engendered a transition from the erstwhile predominant individual-driven scientific endeavors to a prevailing culture of scientific cooperation, which has become instrumental in advancing the frontiers of knowledge (Wuchty et al., 2007). A salient illustration of this evolution lies in the shift from the equal representation of single-authored and team-authored papers in the fields of science and engineering in 1955 to the current scenario, where team-authored works command a dominant 90% share (Cooke & Hilton, 2015). This transformation has been instigated by the escalating intricacy and specialization within scientific research domains (Jones, 2009), coupled with the augmented capital investment in the realm of scientific inquiry (Stephan, 2012). Consequently, the collaborative endeavors of scientists have come to constitute the crucible within which novel knowledge is forged, thereby shaping the trajectory of scientific progress.

Against this backdrop, the generation of new knowledge and the fostering of innovation have become increasingly contingent upon the collective attributes that govern the structure and dynamics of research teams (Fontanarosa et al., 2017; Fortunato et al., 2018). Paramount among these attributes is the age structure of scientific teams (Xu et al., 2024), which exerts an indelible influence on the trajectory of team success (Guimerà et al., 2005; Xu et al., 2022). In a multitude of domains, age has been recognized as a pivotal determinant not only of individual performance but also of team efficacy. The process of aging significantly impacts an individual's physical and cognitive capacities (Guangqi & Tianqu, 2023; Jing et al., 2021), thereby underscoring its relevance to competitive performance and, by extension, the performance of collaborative teams. This principle has been widely embraced in various fields (Mukherjee et al., 2019). The divergence between traditional wisdom and empirical observations invites exploration into the optimal age structure, an inquiry that has garnered substantial attention from researchers spanning diverse fields, including sports, management, psychology, and organizational science (De Meulenaere et al., 2016; Kilduff et al., 2000; Kunze et al., 2011). However, scant attention has been directed toward understanding the nuanced relationship between team age structure and success in the scientific realm.

In this study, we turn our attention to unraveling the influence of age structure within scientific teams on team performance, an inquiry bearing profound implications. Age stands as a foundational demographic attribute among scientists (Cole, 1979; Lehman, 1953; Sugimoto et al., 2016). Given the increasing prominence of collaborative scientific endeavors, insights into the optimal age structure of scientific teams hold paramount significance for the strategic assembly of teams and the enhancement of their performance. Furthermore, the observable trend of scientists aging over time (Jones, 2009; Matthews et al., 2011; Sugimoto et al., 2016) underscores the necessity of maintaining an effective age structure within teams, considering the inevitable progression of seniority within the scientific labor force. Despite the relevance of age structure within scientific teams and the extensive exploration of the link between age and individual scientific achievements, a conspicuous gap exists in our understanding of the ramifications of age structure on scientific team performance. Moreover, a comprehensive and large-scale examination of age structure trends within scientific teams, transcending disciplinary boundaries and spanning extended temporal horizons, remains in its nascent stages.

To address these critical knowledge gaps, our study delves into two facets of age structure within scientific teams, specifically, the average age and age diversity of team members, which collectively reflect variations in age composition. The mean age of team members provides insights into the average accessibility of knowledge, skills, experiences, and other research resources within scientific teams, while also offering an understanding of the average levels of motivation and creative capacity, among other factors influencing

team performance. Age diversity, on the other hand, encapsulates the extent to which scientific teams can harness diversified knowledge and research resources, while considering the potential for conflicts, communication challenges, and coordination issues arising due to the heterogeneity of team members.

In pursuit of this comprehensive inquiry, we pose the following research questions, aiming for a lucid and holistic understanding of the age structure within scientific teams, with a particular emphasis on mean age and age diversity:

RQ1: How has the age structure of scientific teams evolved over time and across fields?
RQ2: What is the relationship between team age structure and scientific impact?
RQ3: What is the relationship between team age structure and scientific disruption?

The subsequent sections of this study are structured as follows: the ensuing section conducts a thorough review of the pertinent literature. "Data and methods" Sect. offers an extensive exposition of data sources and methodology, followed by "Results" Sect., which delineates the principal findings of our study. Finally, the concluding section encapsulates the study's key findings and their broader implications.

Literature review

Age of scientists and scientific performance

The influence of age on the creativity, productivity, and collaborative patterns of scientists has become a focal point in scholarly discourse (Li et al., 2021; Sugimoto et al., 2016). The phenomenon of aging within the scientific community has attracted extensive attention across diverse domains, employing varied analytical approaches and utilizing a rich array of datasets. One notable trend is the inexorable aging of faculty in U.S. universities, colloquially denoted as the "greying effect", primarily attributed to low retirement rates and the deceleration in higher education enrollment (Levin & Stephan, 1989).

Empirical evidence substantiates the unmistakable nature of aging within the scientific domain. Jones (2009) identified a shift toward later ages at which inventors produced their initial patents from 1963 to 1999. Furthermore, Jones (2010) revealed a notable increase of six years in the average age at which Nobel Prize laureates and distinguished inventors achieved their most significant breakthroughs. This upward trajectory is attributed to both an aging population and a delayed initiation of professional careers, with similar trends observed globally. The inevitability of aging within the realm of science has prompted numerous studies exploring its relationship with research performance, specifically focusing on the age at which scientists exhibit peak productivity, creativity, or make their most noteworthy contributions. While some findings exhibit variability influenced by disciplinary distinctions, author nationalities, and cohorts of scientists, a common thread in most extant research is the observation that productivity tends to peak around the midpoint of a scientist's career (Lehman, 2017; Simonton, 1988).

Sunahara et al. (2021) explored how productivity and journal impact intersect across career ages, revealing intriguing dynamics within academia. Their findings suggest that academics tend to resist simultaneous shifts in productivity and journal-prestige levels over consecutive career years. Notably, they observe a rise in productivity with career age, alongside a greater likelihood of achieving high journal impact during early career stages.

Building on this foundation, Sunahara et al. (2023) delved deeper into the nuances of productivity patterns over time. They identified a spectrum of productivity trajectories, including constant, U-shaped, decreasing, periodic-like, increasing, and canonical patterns, with the latter two representing the majority of researchers. Surprisingly, their research challenges conventional assumptions, revealing that productivity peaks often occur around mid-career rather than in the early stages.

Psychologists, sociologists, and economists have proffered diverse explanations for this curvilinear relationship between age and research productivity. Grounded in changes in cognitive and psychological capacities (Lawrence & Blackburn, 1985), knowledge obsolescence (Kyvik & Olsen, 2008), reward systems (Merton, 1957), and incentives (Turner & Mairesse, 2005) across an individual's lifespan, these explanations underscore the gradual process of knowledge accumulation as seniority is attained. According to the cumulative advantage theory (Farys & Wolbring, 2021), senior scientists, occupying higher academic ranks, possess a broader spectrum of intangible resources, including experiences, knowledge, competencies, enriched human and social capital from prior research endeavors (Liu & Hu, 2021, 2022), and heightened familiarity with research domains. However, senior scientists, in contrast to their junior counterparts, grapple with challenges related to cognitive capacities, the risk of knowledge obsolescence, and the potential loss of research interests.

Recent empirical studies have introduced nuance into the age-performance paradigm. An analysis of physicists failed to definitively establish a link between age and high-impact research, suggesting that influential publications are distributed randomly across scientists' academic careers (Sinatra et al., 2016). Studies concerning changes in scientists' careers indicate that scientists have the most focused period in their middle age (Zeng et al., 2019). Moreover, investigations reveal that many successful individuals may experience early career setbacks and subsequently achieve greater accomplishments (Wang et al., 2019; Yin et al., 2019). Furthermore, a recent exploration into the extensive career trajectories of artists, scientists, and film directors demonstrated that periods of exceptional performance, termed "hot streaks," could occur at random junctures throughout scientists' academic careers (Liu et al., 2018, 2021). Remarkably, these "hot streaks" often manifested themselves during the mid-career phase of scientists.

Team age diversity and scientific performance

Age diversity within teams pertains to the distribution of age differences among team members. The scholarship on age diversity within teams is underpinned by two contrasting theoretical perspectives: social categorization theory (Tajfel, 1981; Turner et al., 1987) and the information-processing perspective (Mannix & Neale, 2005; Phillips & O'Reilly, 1998). These theories offer disparate viewpoints on the impact of age diversity on team performance, leading to divergent findings within the empirical literature regarding the relationship between age diversity and team performance and the potential for assembling scientists of different ages to enhance team performance.

The social categorization perspective posits a negative effect of age diversity on team performance, primarily due to intergroup bias disrupting collaborative efforts (Brewer & Kramer, 1985). Individuals naturally tend to categorize others based on shared attributes such as age, leading to the formation of stereotypes (Fiske et al., 2002) and age-based discrimination. This categorization results in reduced cohesion, increased age-related conflicts, and communication challenges, ultimately impeding cooperation among team members (Carton & Cummings, 2012). These negative experiences stemming from age diversity undermine relationships

among team members, hinder the exchange of task-related information, and impede team performance. Several empirical studies support this viewpoint (Kunze et al., 2011; Timmerman, 2000).

Conversely, the information and decision-making perspective suggests a positive effect of age diversity on team performance due to the complementarity of resources among scientists of different ages. The categorization-elaboration model posits that team performance can be enhanced by exchanging, discussing, and integrating diverse ideas, knowledge, and perspectives relevant to team tasks (Kearney et al., 2009; Liu et al., 2022a, 2022b). For example, younger scientists may contribute more to technical tasks, while senior scientists focus on broader conceptual tasks (Larivière et al., 2016). The combination of both young and senior scientists facilitates the achievement of research goals that may involve various types of tasks.

Age-diverse teams offer broader access to task-relevant knowledge, information, skills, and capabilities, thereby facilitating task accomplishment and team performance (Schneid et al., 2016). Additionally, team members from different age cohorts possess distinct work and life experiences, leading to a wider range of task-related ideas and problem-solving abilities (Kunze et al., 2011). Due to the heterogeneity of team members, age diversity reflects complementary knowledge, skills, experiences, and other resources that enhance team effectiveness in performing various tasks (Grant, 1996; Li et al., 2021).

Furthermore, the socioemotional selectivity theory implies complementarity regarding social connections between young and older team members. This theory suggests an age-associated shift in time perspective that influences individuals' pursuit of two goals: knowledge-related goals and emotion-related goals. Young people typically view their future as open-ended, establishing a broader range of social connections beneficial for their career development and knowledge gathering, while older individuals may narrow their social interactions and focus on more targeted connections (Burmeister et al., 2020; Wang et al., 2015a, 2015b). Age-diverse teams could establish complementary social ties that help teams acquire complementary internal and external connections, stimulating team creativity, innovative solutions, and other indicators of team performance (Bantel & Jackson, 1989; Hammermann et al., 2019). This argument finds support in some empirical studies (Kilduff et al., 2000).

Some scholarly inquiries propose that the extremes of age diversity can lead to diminished team performance, as either the resources accessible to teams tend to become excessively homogeneous or conflicts and coordination challenges become excessively prominent (Grund & Westergaard-Nielsen, 2008). However, in the realm of scientific collaboration, team performance is not solely confined to team impact; it also encompasses the potential to disrupt prevailing scientific paradigms (Wu et al., 2019). In this study, we aim to discern not only the associations between team age, team age diversity, and team impact but also to elucidate the connections between team age, team age diversity, and the potential for scientific disruption.

Data and methods

Data source

Our primary data source for this study is the SciSciNet dataset (Lin et al., 2023), which extends the capabilities of the Microsoft Academic Graph (MAG) dataset. The SciSciNet dataset enriches our dataset by providing additional information for each paper, including links to publicly accessible resources. It stands as one of the most cutting-edge datasets in terms of quality and scale, offering a wealth of information for each paper. This information

encompasses crucial attributes such as publication year, paper DOI, paper types, journals, fields, authors, citation links, and various other relevant properties.

Notably, the MAG dataset has already employed advanced deep learning techniques to address the challenge of name disambiguation, and the SciSciNet dataset enhances this by offering more refined information about author career trajectories (Lin et al., 2023). Our research encompasses 134,197,162 authors in the SciSciNet dataset and utilizes their 413,869,501 links to papers to extract author age information.

The SciSciNet dataset provides 19 first-level fields; however, we strategically exclude the fields of Art, Philosophy, and History due to their skewed publication numbers and limited collaboration patterns. Our study therefore focuses on 16 fields, including Mathematics, Physics, Materials Science, Engineering, Computer Science, Geography, Geology, Environmental Science, Chemistry, Medicine, Biology, Psychology, Economics, Business, Political Science, and Sociology.

Furthermore, our analysis centers on 30,056,557 journal research articles published between 1950 and 2017. This temporal constraint serves a dual purpose. First, it enables an adequately extensive citation window for a comprehensive examination of team age and its impact on the realm of science (Bornmann & Tekles, 2019; Wang, 2013). Second, it acknowledges that the scientific landscape underwent significant transformation in the aftermath of World War II, aligning with established research paradigms (Fortunato et al., 2018). Hence, our analysis focuses exclusively on papers published post-1950. The distribution of the data is shown in Figure S1.

Team age diversity

In our analysis, we employ the concept of scientists' academic age, which is defined as the number of years elapsed from their initial publications in the MAG dataset until the year of publication of the focal paper (Milojević, 2012). The mean age of authors in a scientific article team is determined by calculating the average academic age of the authors contributing to a given paper. In line with previous research that assesses age diversity employing the Gini coefficient (He & Huang, 2011), we utilize this index to gauge the level of age diversity within teams. The Gini coefficient serves as one of the most commonly used statistical indices to measure diversity concerning continuous variables, and it has been applied across a variety of domains in prior literature. This index ranges from 0 to 1, with a value of 1 denoting complete homogeneity and a value of 0 indicating maximal diversity.

The Gini coefficient, originally designed to measure income or wealth inequality (Nayak & Gastwirth, 1989), has been increasingly adopted in information science to quantify diversity pertaining to critical aspects of research articles at different levels. For instance, it has been utilized to assess diversity in knowledge integration among papers, a concept known as interdisciplinarity (Leydesdorff, 2018; Leydesdorff et al., 2019; Zhang & Leydesdorff, 2021), the complexity of technologies (Broekel, 2019), the ethnic diversity of authors (AlShebli et al., 2018), and the breadth or depth of research specialization (Chien et al., 2018), among other applications. For instance, the Gini coefficient has commonly been used to capture the uneven distribution of references across various disciplines in a research paper (Leydesdorff & Rafols, 2011; Leydesdorff et al., 2019; Wang et al., 2015a, 2015b).

In the context of a team with n members, the Gini index for team age is defined as follows:

$$Gini\ index = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}|a_i - a_j|}{2n^2\overline{a}} \tag{1}$$

where a_i and a_j represents the age of member i and j, respectively, and $\overline{a}$ denotes the average age of all team members. The Gini index ranges from 0 to 1, with a higher Gini index indicating lower age diversity. To provide a more intuitive measure of the diversity within scientific teams, we define the diversity of team age as:

$$Diversity = 1 - Gini\ index \tag{2}$$

It is noteworthy to mention that we have set the age range of scientists within the interval of 1 to 60. This deliberate choice to commence at 1 ensures that there are no omissions in the results when calculating the Gini index. Conversely, concluding the range at 60 serves to mitigate the potential influence of data errors on our findings, thereby enhancing the robustness of our results.

Variables

To assess team impact, we rely on the metric of the number of citations received by a paper within the first five years of its publication (hereafter C5). C5 measure provides a contemporary evaluation of a paper's scientific influence (Wang, 2013). Focusing on this specific timeframe allows us to capture a snapshot of a paper's impact during a critical period, offering insights into its reception within the scientific community. The distribution of C5 for all 30,233,956 papers across 16 fields over time is shown in Figure S1.

To quantify the interdisciplinary impact of papers, we incorporate the Rao-Stirling index (Stirling, 2007). It is calculated as follows:

$$Interdisciplinarity = \sum d_{ij}p_i p_j \tag{3}$$

where p_i denotes the fraction of citing papers in discipline i, and d_{ij} is the distance between discipline i and j. An interdisciplinarity of 0 reflects a paper with no disciplinary diversity, while an interdisciplinarity of 1 denotes maximal disciplinary diversity. Our study employs 292 second-level disciplines from MAG to compute the interdisciplinarity index. This index captures the balance, variety, and disparity of papers, reflecting the diversity of knowledge sources integrated into the research (Leydesdorff, 2018). It is utilized to account for the interdisciplinary nature of research papers, ensuring that this aspect is comprehensively addressed. Notably, since we use the citation to calculate the interdisciplinarity index, this measure can reflect papers' interdisciplinary impact (Vantard et al., 2023).

We use the Disruption index (also known as the CD index) to quantify the disruption level of papers (Park et al., 2023; Wu et al., 2019). Illustrated in Figure S2, the Disruption index is represented by the following formula:

$$Disruption = \frac{n_{DC} - n_{CC}}{n_{DC} + n_{CC} + n_{RC}} \tag{4}$$

where n_{CC} (consolidating citations) denotes the number of publications referencing both the focal paper (FP) and its sources, while n_{DC} (disruptive citations) represents the count of publications citing FP without referencing its cited sources. Additionally, n_{RC} signifies the count of publications citing FP's sources without referencing FP itself. The Disruption

index carefully scrutinizes the interplay between these citation patterns to gauge the extent of disruption within the scholarly landscape (Yang et al., 2023a, 2023b; Yang et al., 2023a, 2023b). A focal paper that references sources also cited by many of the papers citing FP is perceived as contributing to the consolidation of the existing paradigm, aligning with and reinforcing established knowledge. Conversely, when future citations of the focal paper neglect to acknowledge the sources cited by FP, it signifies the potential disruption of the research paradigm. Such a scenario may herald the emergence of new fields and the reconfiguration of existing knowledge boundaries (Yang et al., 2024).

In our analytical framework, we integrate a set of fundamental control variables that encompass various dimensions of the collaborative nature inherent in scientific research. Firstly, we include the number of references in a scientific paper as a control variable (Yin & Wang, 2017), offering insights into the breadth of the literature reviewed and assimilated into the research. Secondly, we incorporate the average age of references, accounting for the historical context underpinning the research (Mukherjee et al., 2017). Moreover, the length of a paper's title is integrated as a control variable, recognizing its potential influence on the scientific impact within specific contexts (Zhang & Zhu, 2022).

Furthermore, we introduce the author's average past publication counts as a control variable (Azoulay et al., 2019). This metric serves to consider an author's prior research contributions, academic standing, and track record, acknowledging that researchers with varying levels of experience may exert differing impacts on research outcomes. We also incorporate a control variable to assess whether a paper received funding from the National Institutes of Health (NIH) or the National Science Foundation (NSF). This control variable facilitates the evaluation of the potential influence of such notable funding sources on research outcomes (Yang, 2024).

Acknowledging the collaborative nature of scientific research, we account for collaboration through various dimensions. These include the number of authors involved in a research paper, a pivotal factor that recognizes the inherent collaborative effort in the research endeavor (Wuchty et al., 2007). We also consider cross-institutional collaboration (Jones et al., 2008), acknowledging that diverse institutional contributions can significantly impact research outcomes. Furthermore, international collaborations (Wagner et al., 2019) are taken into account, recognizing the global reach and potential impact of such collaborative endeavors. Descriptive statistics of all variables are presented in Table 1.

Econometric model

To scrutinize the intricate relationships between team age and scientific impact, as well as age diversity and scientific impact, we employ a multivariate regression model. C5 is estimated using Eq. 5, with team age serving as the independent variable, representing the average career age of authors in paper i. Year and field fixed effects are included to account for variations attributed to publication year (Y_t) and discipline (F_i) within Eq. 5.

$$C5_i = \alpha + \beta_1 \left(Team\,age_i\right) + \alpha(Controls) + F_i + Y_t + \varepsilon_{it} \tag{5}$$

Recognizing that the relationship between team age and scientific impact may not be strictly linear, we conduct an examination to ascertain whether there exists a curvilinear association between team age and scientific impact. To achieve this, we introduce the square term of team age into the econometric model, as shown in Eq. 6.

Table 1 Descriptive statistics of variables

Variables	Obs	Mean	Std	Min	25Pct	Median	75Pct	Max
5-year citation	30,056,557	14.05	36.98	0	2	6	15	37,405
Interdisciplinarity	29,513,354	0.18	0.08	0	0.13	0.19	0.23	0.46
Disruption	30,056,557	0.001	0.03	− 1	− 0.003	0.000	0.000	1.00
Team age	30,056,557	10.34	7.53	1	4.67	9.4	14.5	59.67
Team age diversity	30,056,557	0.72	0.19	0.23	0.56	0.67	0.91	1
Reference count	30,056,557	27.27	27.23	2	11	21	35	1899
Reference age	30,054,880	10.18	6.07	0	6.29	9	12.6	183.67
Title length	30,056,557	92.39	35.81	4	67	89	114	982
Au past pubs	30,056,557	34.71	52.08	0	4.5	18.33	44.75	3342
Funding (dummy)	30,056,557	0.08	0.27	0	0	0	0	1
#Author	30,056,557	4.02	14.60	1	2	3	5	5104
#Institution	30,056,557	1.44	1.47	1	1	1	2	463
#Country	30,056,557	1.16	0.55	1	1	1	1	69

$$C5_i = \alpha + \beta_1\left(Team\,age_i\right) + \beta_2\left(Team\,age_i^{\,2}\right) + \alpha(Controls) + F_i + Y_t + \varepsilon_{it} \tag{6}$$

Similarly, for investigating the relationship between age diversity and scientific impact, we replace $Team\,age_i$ with $Team\,age\,diversity_i$ in Eqs. 5–6, while simultaneously incorporating team age as a control variable. Additionally, we introduce the square term of age diversity into the econometric model to examine whether a non-linear relationship persists between age diversity and scientific impact.

Moreover, we adopt the same analytical framework using the interdisciplinarity and disruption variables instead of C5 to estimate the relationship between the interdisciplinarity/disruption of papers and the two age-related variables, along with other pertinent factors.

Results

Increasing aging and decreasing age diversity in teams

Our comprehensive analysis of a vast dataset comprising 30,233,956 papers published between 1950 and 2017, as illustrated in Figs. 1 and S3, reveals a striking and compelling trend. The average team age, maximum team age, and minimum team age have all exhibited a discernible upward trajectory over time, with a particularly pronounced increase beginning around 1970. In stark contrast, the trend for team age diversity follows a divergent path, demonstrating a consistent decline over the same temporal span.

These distinct patterns of increasing team age and diminishing age diversity persist consistently across all 16 fields of study. Notably, while significant heterogeneity is observed among different fields concerning team age and diversity, the overarching temporal patterns of both the average team age and team diversity demonstrate remarkable consistency across the papers of all 16 fields. Furthermore, our investigation delves into the temporal patterns concerning papers with various team sizes. We identify a robust correlation between team age and team sizes, indicating that larger teams tend to exhibit higher team age and lower team diversity. Nevertheless, it is important to note that the temporal patterns related to the

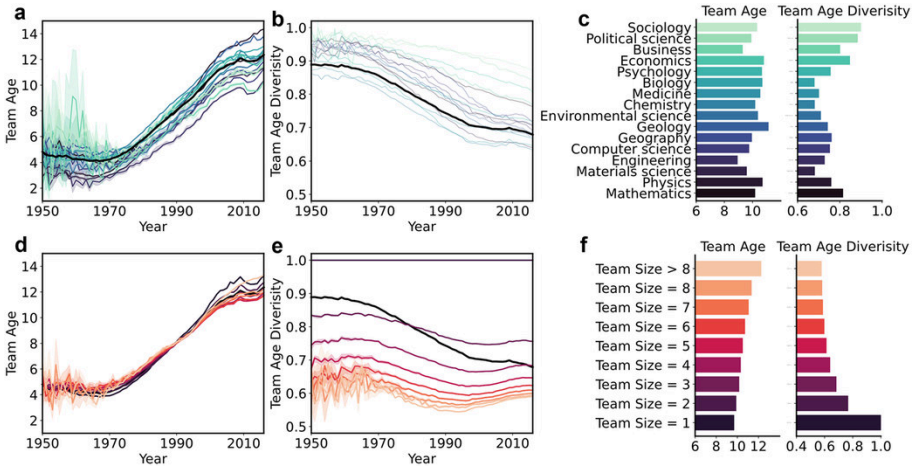


Fig. 1 Temporal trends in team age and diversity: an upward trajectory in average team age and a decreasing trend in team age diversity. **a–c** The temporal evolution of the average team age and team diversity across 16 distinct fields. The black solid lines in (**a–b**) represent the overall trend for all papers, while the other lines depict the trends within each individual field as of panel **c**. **d–f** The temporal patterns of the average team age and team diversity over time concerning different team sizes. Notably, larger teams exhibit higher team age and lower team diversity. The shaded areas in all panels indicate the 95% bootstrap confidence intervals

average team age and team diversity over time remain consistent across papers with different team sizes, except the team diversity of single-author papers.

Team age pattern and scientific impact

We delve into the intricate interplay between the average team age and various facets of team performance. Specifically, we focus on 5-year paper citations, the likelihood of achieving the coveted status of "hit papers" (reserved for the top 5% highly cited papers within a given year and field), and the degree of interdisciplinarity exhibited by papers. The results presented in Fig. 2 provide an encompassing understanding of this relationship, unearthing the presence of an inverted-U relationship between team age and scientific impact.

We discern that as team age advances, the 5-year paper citations display an initial growth phase, subsequently transitioning into a decline. Notably, this turning point becomes evident when the team size reaches approximately 20 (Fig. 3a and 3d). A similar pattern unfolds in the context of the hit rates of papers, with the turning point occurring at a team size of approximately 25 (Fig. 3b and 3e). Remarkably, teams with an average age below eight exhibit hit rates falling below the overall average, whereas teams with an age exceeding eight manifest above-average hit rates.

Furthermore, a comparable pattern emerges when assessing the interdisciplinarity of papers. For papers with a team age under 20, interdisciplinarity tends to increase with team age. Within the team age range of 20 to 50, interdisciplinarity remains relatively stable.

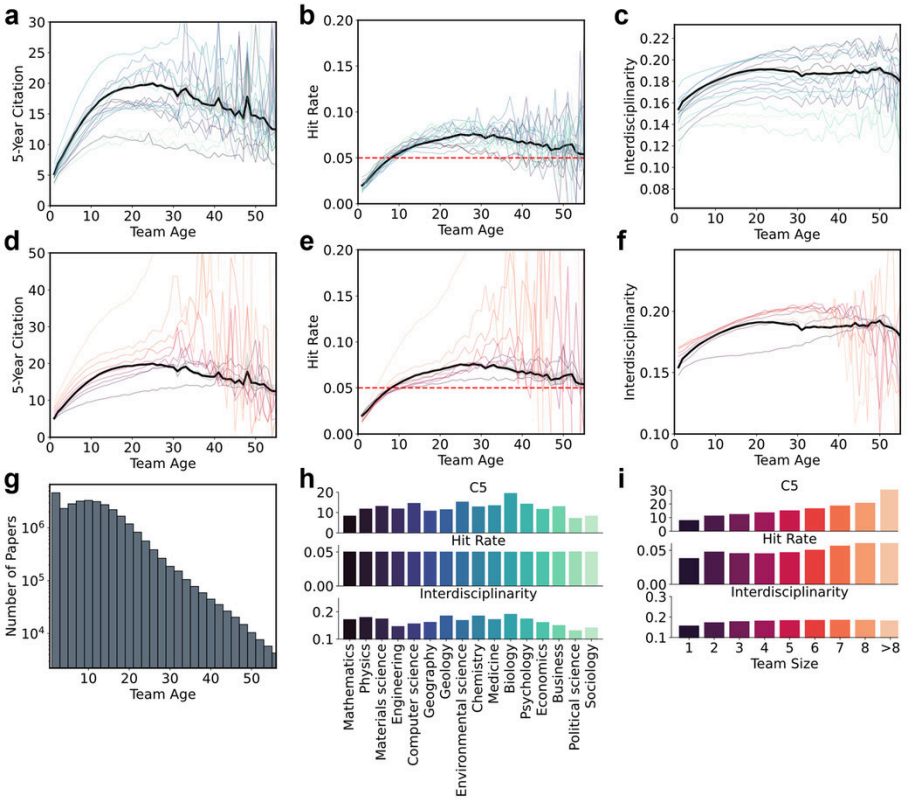


Fig. 2 The inverted-U relationship between team age and scientific impact. **a, d** The relationship between team age and 5-year citations. **b, e** The relationship between team age and hit rates. **c, f** The relationship between team age and interdisciplinarity. **g** The distribution of team age for all papers. **h, i** The distribution of C5, hit rate, and interdisciplinarity across various fields and team sizes. Solid lines in panels (**a–f**) indicate the trends for all papers, while the remaining lines represent the trends within specific fields or team sizes, as denoted in panels (**h, i**). **b**, **e** The dash lines indicate the fraction of hit papers. The shaded areas in all panels indicate the 95% bootstrap confidence intervals

However, for papers featuring a team age surpassing 50, interdisciplinarity exhibits a diminishing trend (Fig. 3c and 3f).

Our observations emphasize significant variations among fields and team sizes, particularly pronounced when the team size exceeds 30. This variability can be attributed, in part, to the skewed distribution of team age, characterized by a long-tail distribution. Additionally, our findings underscore the presence of discernible disparities in scientific impact and interdisciplinarity across different fields and team sizes. Nonetheless, the inverted-U relationship between scientific impact and team size remains consistent across various fields and team sizes.

Figure 3 unveils that the connection between team age diversity and scientific impact follows an inverted-U relationship, albeit lacking clear-cut turning points. We observe that highly diverse teams (characterized by team age diversity exceeding approximately 0.95) and low-diversity teams (with team age diversity lower than approximately 0.45) exhibit conspicuously low 5-year citations, hit rates, and interdisciplinarity.

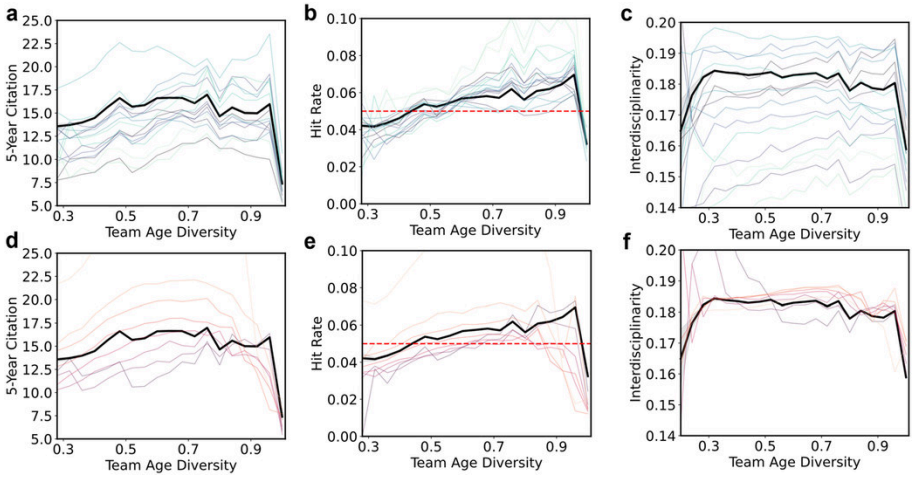


Fig. 3 The inverted-U relationship between team age diversity and scientific impact. **a, d** The relationship between team diversity and 5-year citations. **b, e** The relationship between team diversity and hit rates. **c, f** The relationship between team diversity and interdisciplinarity. **a–f** The solid lines indicate the trends for all papers, while the remaining lines represent the trends within specific fields or team sizes. **b**, **e** The dash lines indicate the fraction of hit papers. The shaded areas in all panels indicate the 95% bootstrap confidence intervals

In contrast, moderately diverse teams manifest relatively high scientific impact and interdisciplinarity.

Within the cohort of moderately diverse teams, some fluctuations are discernible in the relationship between team diversity and scientific impact. Additionally, we find a considerable degree of heterogeneity in these relationships across fields and team sizes. Nevertheless, the inverted-U relationship remains robust and consistent across various fields and team sizes.

We conducted a series of regression analyses aimed at elucidating the intricate relationships between team age and scientific impact, as well as between team age diversity and scientific impact. These analyses incorporated a comprehensive array of pertinent variables, including the level of collaboration, reference count and age, title length, fields, and year. The results of these analyses are presented in Tables 2 and 3.

Models (1–3) reveal that, overall, the coefficients for team age demonstrate a significant positive association with the 5-year citation count and interdisciplinarity. In contrast, the coefficients for team age diversity exhibit a noteworthy negative relationship with the 5-year citation count and interdisciplinarity.

Upon the addition of the quadratic coefficients, Models (4–7) within Table 2 and Table 3 serve to corroborate the existence of the inverted-U relationship between team age and scientific impact, as well as the presence of the inverted-U relationship between team age diversity and scientific impact. These results suggest that to achieve the highest scientific impact, moderate team age and team age diversity represent the optimal choice.

Table 2 Inverted-U relationship between team age, team age diversity and 5-year citation

Models	(1) log (C5)	(2) log (C5)	(3) log (C5)	(4) log (C5)	(5) log (C5)	(6) log (C5)	(7) log (C5)
Team age	0.0091*** (2.89e-5)		0.0089*** (2.9e-5)	0.0229*** (6.18e-5)		0.0084*** (2.93e-5)	0.0209*** (6.64e-5)
Team diversity		−0.1611*** (0.0011)	−0.1423*** (0.0011)		0.9970*** (0.0078)	0.6596*** (0.0079)	0.3752*** (0.0080)
Team age^2				−0.0005*** (1.81e-6)			−0.0004*** (1.93e-6)
Team diversity^2					−0.8037*** (0.0053)	−0.5572*** (0.0054)	−0.3109*** (0.0055)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	30,054,880	30,054,880	30,054,880	30,054,880	30,054,880	30,054,880	30,054,880
R2	0.3277	0.3260	0.3281	0.3292	0.3265	0.3283	0.3293

All models are based on OLS regression. Standard errors are in parentheses. In our regression analyses, we employ the natural logarithm of C5, which is represented as ln(C5 + 1).The negatively significant coefficient of the square term of team age in models (4) and (7) indicates an inverted-U relationship between team age and 5-year citation. Similarly, the negatively significant coefficient of the square term of team age diversity in models (5)–(8) suggests an inverted-U relationship between team age diversity and 5-year citation

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table 3 Inverted-U relationship between team age, team age diversity and interdisciplinarity

Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Interdisciplinarity (Pct.)	Interdisciplinarity (Pct.)	Interdisciplinarity (Pct.)	Interdisciplinarity (Pct.)	Interdisciplinarity (Pct.)	Interdisciplinarity (Pct.)	Interdisciplinarity (Pct.)
Team age	0.0628*** (0.0007)		0.0569*** (0.0007)	0.3529*** (0.0016)		0.0491*** (0.0007)	0.2939*** (0.0017)
Team diversity		−4.733*** (0.0287)	−4.620*** (0.0287)		10.19*** (0.1937)	8.219*** (0.1959)	2.654*** (0.1988)
Team age^2				−0.0096*** (4.56e-5)			−0.0079*** (4.85e-5)
Team diversity^2					−10.37*** (0.1331)	−8.929*** (0.1348)	−4.114*** (0.1379)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	29,511,904	29,511,904	29,511,904	29,511,904	29,511,904	29,511,904	29,511,904
R2	0.3586	0.3591	0.3592	0.3596	0.3592	0.3593	0.3599

All models are based on OLS regression. Standard errors are in parentheses. The interdisciplinarity (pct.) is the percentile value of the Rao-Stirling index, ranging from 0 to 100. The negatively significant coefficient of the square term of team age in models (4) and (7) indicates an inverted-U relationship between team age and interdisciplinarity. Similarly, the negatively significant coefficient of the square term of team age diversity in models (5)–(8) suggests an inverted-U relationship between team age diversity and interdisciplinarity

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Team age pattern and scientific disruption

As shown in Fig. 4, we reveal a U-shaped relationship between disruption and team age, with the turning point occurring at an average team age of approximately 16. This suggests that both excessively young and overly mature teams may exhibit higher levels of disruption, while teams with moderate age composition tend to demonstrate lower disruption levels.

Additionally, our investigation uncovers a U-shaped relationship between disruption and team age diversity. Notably, we observe that teams with extremely high or low age diversity tend to experience increased disruption, whereas teams with moderate age diversity exhibit comparatively lower disruption levels.

Furthermore, we note a strong correlation between disruption and team size, indicating that larger teams tend to experience lower levels of disruption. Our analysis also highlights considerable heterogeneity in the relationship between disruption and team characteristics across different fields. Despite these variations, the consistent presence of the U-shaped relationship between disruption and both team age and team age diversity remains robust across diverse fields and team sizes.

Table 4 presents the regression results highlighting the U-shaped relationship between team age, team diversity, and disruption. Models (1–3) elucidate a significant negative association between team age and disruption. Conversely, the coefficients for team age diversity demonstrate a notable positive relationship with disruption.

The introduction of quadratic coefficients in Models (4–7) serves to reinforce the presence of the U-shaped relationship between team age and disruption, as well as the U-shaped relationship between team age diversity and disruption. These results suggest that teams characterized by extreme age patterns, either excessively old or exceedingly

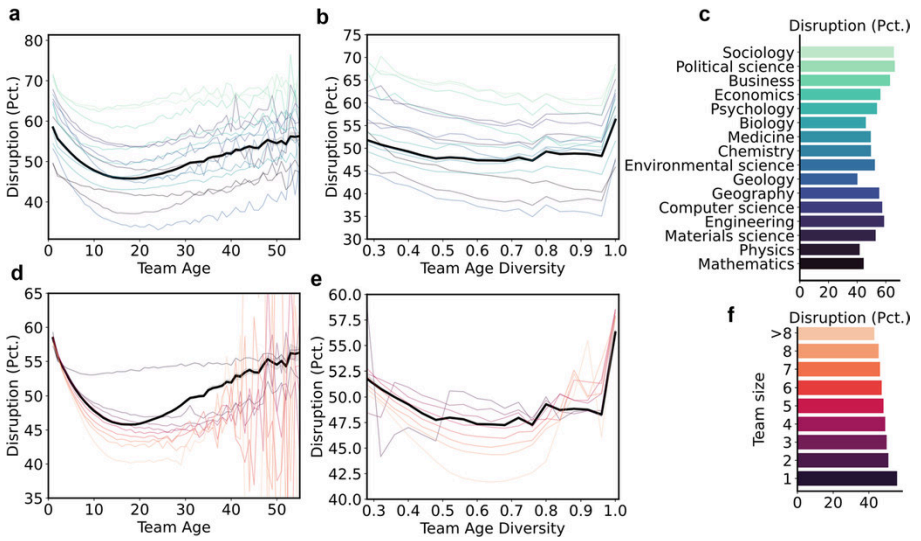


Fig. 4 The U-shaped relationship between team age patterns and scientific disruption. **a, d** The relationship between the average team age and disruption. **b, e** The relationship between team age diversity and disruption. **c, f** The distribution of disruption across various fields and team sizes. Solid lines in panels **a, b, d, e** indicate the trends for all papers, while the remaining lines represent the trends within specific fields and team sizes. The shaded areas in all panels indicate the 95% bootstrap confidence intervals

Table 4 U-shaped relationship between team age, team age diversity and disruption

Models	(1) Disruption (Pct.)	(2) Disruption (Pct.)	(3) Disruption (Pct.)	(4) Disruption (Pct.)	(5) Disruption (Pct.)	(6) Disruption (Pct.)	(7) Disruption (Pct.)
Team age	−0.1997*** (0.0009)		−0.1948*** (0.0009)	−0.5410*** (0.0019)		−0.1766*** (0.0009)	−0.4674*** (0.0020)
Team diversity		4.019*** (0.0344)	3.606*** (0.0345)		−33.84*** (0.2333)	−26.73*** (0.2358)	−20.13*** (0.2392)
Team age^2				0.0113*** (5.43e-5)			0.0094*** (5.78e-5)
Team diversity^2					26.27*** (0.1601)	21.08*** (0.1621)	15.36*** (0.1658)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	30,054,880	30,054,880	30,054,880	30,054,880	30,054,880	30,054,880	30,054,880
R2	0.0910	0.0899	0.0914	0.0923	0.0907	0.0919	0.0927

All models are based on OLS regression. Standard errors are in parentheses. The disruption (pct.) is the percentile value of the Disruption index, ranging from 0 to 100. The negatively significant coefficient of the square term of team age in models (4) and (7) indicates a U-shaped relationship between team age and disruption. Similarly, the negatively significant coefficient of the square term of team age diversity in models (5)–(8) suggests an inverted-U relationship between team age diversity and disruption

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

young, and extreme diversity patterns, either highly diverse or notably homogeneous, tend to exhibit heightened levels of disruption.

Discussion and conclusion

This study delves into the pivotal role of age composition within scientific teams in shaping team performance and scientific impact. Over time, there has been a discernible upward trend in the average age of scientific teams, accompanied by a corresponding decline in team age diversity. Intriguingly, the research uncovers an inverted-U relationship between team age and various dimensions of scientific impact, with the precise turning points contingent upon team size. Similarly, an inverted-U pattern is observed between team age diversity and scientific impact, where teams exhibiting extreme diversity levels, whether excessively diverse or notably homogeneous, display lower impact, while moderately diverse teams demonstrate heightened performance.

Conversely, the analysis reveals a U-shaped relationship between team age and team age diversity and disruption, suggesting that teams characterized by extreme age structures are more prone to disrupting established scientific paradigms. These findings hold robustly across diverse fields and team sizes, offering valuable insights for optimizing scientific team composition and enhancing overall performance in the dynamic landscape of collaborative scientific research.

The implications of this paper are multifaceted and bear significant relevance for the scientific community, research organizations, and policymakers alike. The discerned inverted-U relationship between team age and scientific impact underscores the critical importance of achieving a balanced team composition. Research teams must carefully navigate the trade-off between the accumulated knowledge and experience of senior members and the fresh perspectives and innovation that younger team members can offer. This finding emphasizes the need for a nuanced approach to team building, where scientific leaders and administrators must consider not only the age but also the diversity of team members to optimize scientific productivity and creativity. Moreover, the observed relationship between team age diversity and scientific impact underscores the value of maintaining a moderate level of age diversity within scientific teams. Highly homogenous or excessively diverse teams seem to face challenges in achieving high levels of scientific impact, highlighting the importance of fostering a diverse team with a measured degree of age heterogeneity to yield superior research outcomes. Consequently, organizations and institutions should actively promote inclusivity and consider the age dimension when forming research teams.

Additionally, the U-shaped relationship between team age and team age diversity with disruption calls for careful consideration in managing scientific teams. Extreme age structures, whether characterized by excessive age homogeneity or extreme diversity, are associated with increased levels of disruption within the scientific landscape. Acknowledging and addressing the potentially disruptive forces linked to these team structures can lead to more effective strategies for managing research paradigms and facilitating smoother transitions between scientific developments.

It is also important to acknowledge several limitations in this study. Firstly, the analysis primarily relies on quantitative data, and there may be qualitative aspects of team dynamics and age-related factors that were not fully captured. Secondly, our analysis does not establish a causal relationship but rather demonstrates an association through regression

analysis. Thirdly, while we identify a U-shaped relationship between team age, team age diversity, and disruption, the underlying mechanisms and reasons remain unclear. The research also does not delve deeply into the specific mechanisms through which team age and diversity influence scientific impact, leaving room for further exploration in this regard. Furthermore, while the study examines a broad range of fields and team sizes, there may be nuances within specific disciplines and team structures that were not fully addressed.

Looking ahead, future studies could employ more qualitative approaches, including interviews or surveys, to delve into the subjective experiences of scientists within teams, allowing for a richer understanding of the dynamics at play. Additionally, investigating the role of leadership and mentorship within age-diverse teams could provide valuable insights into how teams can leverage the strengths of members at different career stages. Furthermore, as the scientific landscape continues to evolve, with increasing emphasis on interdisciplinary research and global collaboration, exploring how age structure and diversity influence these trends is a compelling area for future investigation. Finally, considering the implications of these findings for science policy and team assembly could have practical implications for enhancing the effectiveness of collaborative research in the future.

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Code availability We have made all the codes used to redraw the figures and reconduct the analysis in our paper publicly available at https://github.com/AlexJieYang/team-age-structure.

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