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RESEARCH ARTICLE

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Quantifying the dynamics of research teams' academic diversity

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Abstract

The growing complexity of modern scientific challenges demands research teams that integrate diverse perspectives, yet the role of academic status diversity—variation in team members' scholarly achievements—remains insufficiently understood. This study aims to bridge this gap by examining the dynamics of academic diversity within research teams and its association with innovation, analyzing more than 17 million articles across 292 fields. We introduce new metrics—academic entropy, academic standard deviation, and academic disparity—to capture the heterogeneity of team members' academic backgrounds. Using a network null model to account for temporal and disciplinary differences, we uncover significant increases in academic diversity, particularly within STEM fields and developed regions, where diversity levels are notably overrepresented. While we find a positive correlation between academic diversity and interdisciplinarity, higher diversity is associated with lower levels of scientific disruption. Teams with greater academic diversity tend to be associated with consolidating existing knowledge rather than producing disruptive innovations that challenge prevailing frameworks. This trend is especially evident in larger teams, where diversity is linked to incremental progress rather than transformative breakthroughs. These findings underscore the need for a balanced approach to promoting diversity in relation to scientific advancement.

1 | INTRODUCTION

In recent years, the complexity and interconnectivity of scientific challenges have necessitated a paradigm shift in the composition of research teams (Andalón et al., 2024; Fortunato et al., 2018; Jones et al., 2008; Lin et al., 2023; Wu et al., 2019; Wuchty et al., 2007; Xu, Wu, & Evans, 2022; Yang, Ding, & Liu, 2024). Modern scientific

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endeavors, such as the application of artificial intelligence for science (AI4S) and breakthroughs in quantum computing technology, exemplify this complexity. AI4S, which leverages machine learning to accelerate discoveries in fields like drug development and materials science, benefits from teams that blend early-career researchers—who often explore novel AI-driven hypotheses due to their agility and lower stakes—with established scholars, whose high academic status provides authoritative validation and access to extensive research networks (Andalón et al., 2024; Wang et al., 2023; Xing et al., 2025). Similarly, advancing quantum computing requires a blend of junior researchers, who are often more willing to explore unconventional approaches, and senior scientists, who provide strategic guidance and access to critical resources based on their extensive academic achievements. These examples underscore the importance of academic status diversity—the inclusion of team members with varying levels of academic achievements—in fostering innovative solutions to multifaceted problems. As a result, academic diversity has emerged as a critical factor influencing scientific productivity and innovation (Andalón et al., 2024; Li et al., 2022; Xing et al., 2025).

In recent years, the complexity and interconnectivity of scientific challenges have necessitated a paradigm shift in the composition of research teams (Andalón et al., 2024; Fortunato et al., 2018; Jones et al., 2008; Lin et al., 2023; Wu et al., 2019; Wuchty et al., 2007). Modern scientific endeavors, such as the application of AI4S and breakthroughs in quantum computing technology, exemplify this complexity. AI4S, which leverages machine learning to accelerate discoveries in fields like drug development and materials science, is associated with teams that blend early-career researchers—who often explore novel AI-driven hypotheses due to their agility and lower stakes—with established scholars, whose high academic status is linked to authoritative validation and access to extensive research networks (Andalón et al., 2024; Wang et al., 2023; Xing et al., 2025). Similarly, advancing quantum computing is associated with a blend of junior researchers, who are often more willing to explore unconventional approaches, and senior scientists, who are linked to strategic guidance and access to critical resources based on their extensive academic achievements. These examples underscore the importance of academic status diversity—the inclusion of team members with varying levels of academic achievements—in relation to innovative solutions to multifaceted problems. As a result, academic diversity has emerged as a critical factor associated with scientific productivity and innovation (Andalón et al., 2024; Li et al., 2022; Xing et al., 2025).

Historically, research team composition has often favored homogeneity, potentially limiting creativity and innovation. Early studies have demonstrated that diversity—across nationality (Hsiehchen et al., 2015; Lin et al., 2023), academic discipline (Liu et al., 2024), or gender (Yang et al., 2022)—is associated with richer exchanges of ideas and linked to creative solutions. Within this context, academic diversity encompasses not only the representation of different fields of study but also the varying levels of expertise, experiences, and perspectives contributed by team members. As the importance of diverse viewpoints in relation to innovative solutions gains recognition, systematically measuring and analyzing the dynamics of academic diversity within research teams becomes essential.

Despite the recognized importance of academic diversity, empirical investigations into its dynamics and relationship with scientific innovation remain sparse, particularly when utilizing citation-based measures. Citations serve as a fundamental evaluative metric for scholars in most universities and can effectively function as a proxy for academic status (Fortunato et al., 2018). Existing literature has predominantly focused on aspects of team diversity—such as gender, race, discipline, affiliation, and nationality—while neglecting analyses centered on academic status. Furthermore, there is a lack of attention to the dynamics of individual performance within diverse teams, often overlooking the broader implications of academic diversity for innovation outcomes. The mechanisms through which academic diversity is associated with scientific disruption and innovative capacity remain particularly underexplored (Funk & Owen-Smith, 2017; Park et al., 2023; Yang, 2025a), presenting a compelling opportunity to assess how varying levels of academic diversity within research teams are linked to groundbreaking scientific contributions.

This study addresses two critical gaps in the literature: (1) the lack of empirical investigations into the dynamics of academic status diversity within research teams, and (2) the underexplored relationship between academic status diversity and scientific innovation. Specifically, we ask: How has academic status diversity evolved over time and across scientific disciplines? What is the association of academic status diversity with scientific disruption, a key indicator of innovation? Furthermore, how are factors such as team size, interdisciplinarity, and regional disparities associated with these dynamics and relationships?

By answering these questions, our research contributes to a deeper understanding of how diverse research teams function and their association with scientific progress. We introduce novel metrics—academic entropy, academic standard deviation, and academic disparity—to capture the heterogeneity in team members' academic statuses, providing a more nuanced analysis than traditional diversity measures. Using a comprehensive dataset of over 17 million scholarly articles across 292 disciplines and employing a network null model to control for

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citation variations, we ensure the robustness of our findings. Ultimately, this study not only advances theoretical discussions on academic status diversity but also offers practical insights in relation to promoting innovation through strategic team composition.

2 | BACKGROUND

2.1 | Team academic diversity

Recent studies underscore the evolving dynamics of scientific collaboration, with a marked shift toward co-authorship among researchers. Modern scientific fields are increasingly engaging in joint authorship, yielding significant impact advantages (Jones, 2021). While this "rise of teams" facilitates the amalgamation of diverse perspectives, knowledge, and skills, it simultaneously presents challenges, particularly in the division of credit, which can impede individual career progression.

Milojević (2014) distinguishes between two modes of knowledge production: small, core teams versus extended teams that grow based on prior productivity. Wuchty et al. (2007) corroborate that teams, particularly larger ones, produce more frequently cited research than individuals, with this trend intensifying over time. This shift poses critical questions about individual contributions within teams and the mechanisms underlying collective research success. Ahmadpoor and Jones (2019) further elucidate the impact advantages of teamwork, noting that these benefits diminish as the citation indices among team members diverge. They suggest that lower-citation members play a pivotal role in determining overall team impact, centering around the harmonic mean of individual citation metrics. Moreover, studies by Sauermann and Haeussler (2017) and Xu, Wu, and Evans (2022) explore the complexities of team dynamics, revealing how leadership roles and individual contributions coalesce to shape team outcomes.

Zeng et al. (2021) illuminate the importance of team member freshness as a crucial indicator of research originality and multi-disciplinarity, surpassing the traditional metric of novel collaboration relationships. This suggests that the influx of new members enhances the innovative capacity of research teams. Concurrently, Jones et al. (2008) demonstrate that collaborations extending beyond university boundaries yield the highest-impact publications, highlighting the significance of interdisciplinary and multi-institutional efforts. Hsiehchen et al. (2015) further corroborate these findings, revealing that diverse international collaborations contribute to enhanced citation outcomes, albeit with diminishing returns on citation rates as team sizes increase.

Andalón et al. (2024) indicate that larger team sizes at the time of graduation negatively affect scientists' career prospects. As team size has increased across fields, individuals have become less likely to secure tenure-track positions, receive tenure, or obtain federal research funding. These individuals are also more likely to leave academia and their scientific field. Xing et al. (2025) find that mentees trained in larger groups tend to exhibit superior academic performance compared to those from smaller groups, provided they remain in academia after graduation. However, their study also uncovers unexpected trends: mentees from larger groups have significantly lower academic survival rates, and mentees with highly productive mentors also experience lower academic survival rates. While these studies analyze the relationship between career success and academic diversity within fields, no research has yet examined the connection between academic diversity and innovation.

AlShebli et al. (2018) delve into the implications of diversity within research teams, revealing a strong correlation between ethnic diversity and scientific impact, while also identifying instances of homophily that can limit diversity. Additionally, Li et al. (2019) emphasize that junior researchers who collaborate with established scientists gain a persistent competitive advantage throughout their careers. Xu, Bu, et al. (2022) examine team age as a measure of power hierarchy, proposing that a flat team structure correlates with enhanced impact, especially in high-power teams. Yang, Xu, et al. (2024) also use team academic age to measure hierarchy or diversity. Building upon this, our study posits that citation-based measures more accurately reflect academic status than team age alone, given the reliance on citations as a metric of recognition in the scientific community (Fortunato et al., 2018).

Given the complexities identified in prior research, our study will utilize total citation counts as a proxy for academic status and will employ diversity measures such as entropy and standard deviation to quantify team diversity. We hypothesize that team academic diversity, akin to other diversity metrics, will exhibit an increasing trend over time. Additionally, we anticipate a positive correlation between team academic diversity and both paper interdisciplinarity and other diversity measures. To investigate these hypotheses, we will utilize randomized baseline models and regression analysis, ultimately seeking to delineate the intricate relationships between team composition, diversity, and research impact.

2.2 | Scientific disruption

An important dimension of our research involves investigating the relationship between team academic diversity

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and scientific disruption. Our analysis employs the recently developed yet widely adopted CD index, introduced by Funk and Owen-Smith (2017). This metric, grounded in the structural analysis of the deep citation network, provides a systematic approach to assess the disruptive nature of academic papers by quantifying the alignment of a paper with established knowledge alongside its potential to induce paradigm shifts. The CD index thus offers a novel lens for evaluating scholarly innovation (Bornmann et al., 2020). Funk and Owen-Smith (2017) argue that the CD index captures (i) the extent to which future inventions build on prior technologies, (ii) variations in how an invention modifies the use of its predecessors over time, (iii) degrees of consolidation and destabilization from large-scale transformations to incremental shifts, and (iv) the distinction between consolidating and destabilizing technologies that may exhibit similar impacts. Further studies suggest that different collaborative patterns yield varying degrees of disruptive potential (Wu et al., 2019; Yang, Gong, et al., 2024).

Recent investigations have increasingly connected the CD index with team diversity metrics, prompting our exploration of this relationship as it pertains to team academic diversity. Wu et al. (2019) demonstrate that smaller teams tend to introduce disruptive ideas and opportunities, while larger teams often focus on the development of existing concepts. Contributions from larger teams are more closely aligned with contemporary advancements, garnering immediate attention, whereas smaller teams delve deeper into past knowledge, resulting in disruptive innovations that gain significance over time. Xu, Wu, and Evans (2022) find that tall, hierarchical teams produce less novelty and often reiterate existing ideas, enhancing productivity for senior members while diminishing it for junior members, thereby increasing short-term citations but reducing long-term impact. Lin et al. (2023) observe that across diverse fields, periods, and team sizes, remote teams are consistently less likely to achieve breakthrough discoveries compared to their on-site counterparts. Liu et al. (2024) categorize articles based on authors' affiliations, revealing that monodisciplinary collaborations tend to be more disruptive than multidisciplinary ones.

Based on these findings, we hypothesize that greater team academic diversity correlates with lower disruptive potential; conversely, flatter academic teams are more likely to develop or consolidate existing ideas. Notably, researchers have raised concerns regarding potential biases in the CD index linked to reference counts (Leibel & Bornmann, 2024; Yang, Gong, et al., 2024; Yang, Yan, et al., 2024). While acknowledging the limitations of the CD index, our aim is not to address these shortcomings in the current study but to provide initial insights. Moreover, this research is not causal in nature; rather, it serves as a comprehensive analysis of the trends, distributions, and fundamental properties associated with team academic diversity.

3 | DATA AND METHODS

3.1 | Data

This study makes use of the Microsoft Academic Graph (MAG), which is well-known for its broad coverage of scientific literature (Wang et al., 2020). The MAG dataset includes metadata for over 200 million scholarly works and more than 1.7 billion citation links. Our analysis focuses on journal articles published between 1970 and 2015, as data outside this range, particularly after 2015 and before 1970, is less complete in MAG. Additionally, author disambiguation is more reliable within this time frame. We limit our analysis to team papers, defined as those with at least two authors, resulting in a final sample size of 17,161,020 papers.

The metrics we use heavily depend on author publication histories to track dynamic citation counts by year. MAG's name disambiguation process is highly accurate, utilizing advanced machine learning algorithms (Wang et al., 2020). MAG provides detailed metadata for each paper, such as publication year, DOI, paper type, journal or conference, citation links, funding information, and other attributes. Our analysis adopts a hierarchical classification based on MAG's taxonomy. The first classification level includes 19 major disciplines like Medicine, Physics, and Computer Science, while the second level consists of 292 subfields. Each paper is assigned one or more field labels through a machine learning model, with confidence scores ranging from zero to one. For this analysis, we focus on the first and second-level classifications (19 major fields and 292 subfields) and prioritize the label with the highest confidence when multiple labels are assigned.

3.2 | Quantifying academic diversity

This paper presents a methodological framework for evaluating the academic diversity of scientific teams. For a given paper i, let the set of contributing authors be denoted as $A_i = \{a1, a2, ...\}$. For each author ak, we compute their cumulative citation count prior to the publication of the focal paper, denoted as cit_{ak}. To mitigate the effects of skewness in citation distributions, a logarithmic transformation is applied, such that $c_{ak} = ln(cit_{ak} + 1)$, which serves as a proxy for the author's academic status.

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The academic status of the entire team for paper i is then represented as the vector $C_i = \{c_{a1}, c_{a2}, ..., c_{ak}, ...\}$.

We propose three novel measures to quantify academic diversity: academic entropy, academic standard deviation, and academic disparity. Academic entropy is rooted in information theory, specifically Shannon entropy, and is calculated as:

$$\text{Academic entropy} = -\sum_{c \in C_i} p_c ln(p_c),$$

where $c \in C_i$ represents the academic status of an individual team member for paper i, p_c denotes the probability distribution of authors according to their academic status. This metric quantifies the heterogeneity of academic statuses by measuring the uncertainty in their distribution. Unlike other diversity indices (e.g., Gini coefficient or simple counts of unique categories), academic entropy leverages information theory to capture the full spectrum of variation in a continuous, citation-based measure of academic status. Its unique advantage lies in its sensitivity to the shape of the distribution—distinguishing between teams with evenly distributed statuses versus those dominated by a few outliers—offering a more nuanced view of intellectual heterogeneity compared to binary or categorical approaches.

Academic standard deviation (Academic std) is defined as the standard deviation of the academic statuses in C_i, reflecting the dispersion of expertise within the team. This indicator complements academic entropy by providing a straightforward statistical measure of variability, rooted in descriptive statistics. It highlights how spread out the team's academic statuses are around the mean, offering a practical lens on the range of scholarly experience and recognition within the group. Its advantage lies in its interpretability and alignment with conventional measures of spread, making it accessible for comparing teams across contexts.

Academic disparity is measured as the maximum difference in academic status between any two members of the team, that is, $\max(C_i) - \min(C_i)$. This indicator captures the extent of inequality or power asymmetry in academic standing, drawing from sociological theories of status hierarchies. Its strength is in revealing extreme differences that might influence team dynamics, such as decision-making or credit allocation, which entropy or standard deviation might underemphasize due to their focus on overall distribution or average spread.

3.3 | Null models: Reshuffled data

Raw academic diversity measures cannot be directly used to analyze temporal trends or field-specific distributions due to the heterogeneous nature of citation counts across time and disciplines. To account for these variations, we employ a null model as a control mechanism. In the field of science, null models serve as baselines for assessing the significance of observed patterns by reshuffling data (Cimini et al., 2019). This method has been widely adopted in network-based and career-level analyses (Liu et al., 2018; Park et al., 2023; Yang, 2025c; Zeng et al., 2019).

The null model approach involves randomizing key attributes of the dataset while preserving its overall structural properties and statistical distributions, thereby disrupting any inherent correlations. This allows for the identification of patterns that are not merely artifacts of random variation. By comparing the empirical results with the outcomes generated from the null model, researchers can rigorously evaluate the significance of their findings, ensuring that the detected relationships are reflective of real, underlying mechanisms rather than stochastic noise.

In our study, we randomly reshuffle the paper-author data while controlling for the publication year, the authors' home field, and the team size for each paper. Specifically, authors of a paper in a given year and field are randomly assigned to a different paper within the same constraints. From this reshuffled dataset, we calculate the expected academic diversity values for each year and field. The difference between the observed values from the empirical data and the expected values derived from the null model provides the basis for testing our hypothesis:

$$\Delta = obs_{\text{group}} - exp_{\text{group}}.$$

This approach ensures that any observed deviations are robust and not the result of random fluctuations, enabling a more accurate interpretation of the results.

3.4 | Related measures

3.4.1 | Other team diversity measures

This study explores the relationship between team academic diversity and other dimensions of team diversity, paper interdisciplinarity, and scientific disruption. To assess other team diversity, we incorporate variables reflecting team age, nationality, academic field, and gender composition. Specifically:

Team age entropy is calculated as $-\sum p_{age} \ln\left(p_{age}\right)$, where academic age is defined as the number of years since an author's first publication in the MAG dataset. The range for academic age is set between 0 and 60 years,

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with 60 serving as an upper limit to address potential data inaccuracies (Yang, Xu, et al., 2024).

Team internationalism is measured as $ln(\#Countries)$, representing the natural logarithm of the number of countries represented by the team members' affiliations (Hsiehchen et al., 2015).

Team field entropy is calculated as $-\sum p_{field} \ln\left(p_{field}\right)$, where p_{field} denotes the proportion of team members whose primary field corresponds to the 19 top-level MAG fields of study. This metric captures the distribution of expertise across different scientific domains within the team (Liu et al., 2024).

Team gender entropy is assessed using the Shannon entropy formula $-p_f ln\left(p_f\right) - \left(1-p_f\right) ln\left(1-p_f\right)$, where p_f represents the proportion of female authors within the team. Gender entropy ranges from 0 to 1, with higher values indicating greater gender diversity. A value of 0 indicates a team composed entirely of either men or women, while values closer to 1 reflect a more balanced gender composition (Yang et al., 2022).

3.4.2 | Interdisciplinarity

To assess paper interdisciplinarity (Stirling, 2007), we draw on MAG's 292 secondary disciplines. For each paper i and its set of references $R_i = \{r1, r2, ...\}$, the fields of the references are mapped into a field distribution vector $F_i = \{field_{r1}, field_{r2}, ..., field_{rk}, ...\}$, where $field_{rk}$ reflects the field of reference r_k.

Interdisciplinary variety is represented by the number of fields covered by the references of paper i, defined as $ln\left(\sum_{r \in R_i} field_r\right)$.

Interdisciplinary entropy is defined as $-\sum p_m ln(p_m)$, where $m \in F_i$ represents a field of the references of paper i, p_m represents the probability of references in that field.

Interdisciplinary disparity is represented by the maximum distance between fields present in the references of paper i, defined as $Max\{d_{mn} | m, n \in F_i\}$. where d_{mn} is derived from MAG's large-scale co-citation matrix, constructed using over 1.5 billion citation links spanning from 1800 to 2021. The cosine distance between co-citation vectors V_m and V_n quantifies knowledge interactions across fields, enabling the calculation of d_{mn}.

The Rao-Stirling index is defined as $\sum_{m \neq n} d_{mnt} p_m p_n$, where p_m denotes the fraction of references in discipline m, and d_{mnt} is the distance between field m and n in year t.

3.4.3 | Disruption

The CD index (Funk & Owen-Smith, 2017; Park et al., 2023) quantifies the degree to which an idea disrupts the current state of science or technology. It is defined as $\frac{n_{DC}-n_{CC}}{n_{DC}+n_{CC}+n_{RC}}$, where n_{DC} (the number of disruptive citations) represents the count of publications citing the focal paper without referencing its cited sources, n_{CC} (the number of consolidating citations) denotes the count of publications citing the focal paper and its references, and n_{RC} represents the number of publications citing the focal paper's references without citing the focal paper itself. A lower CD index suggests extensive citation of references aligning with established knowledge, whereas higher values indicate papers with the potential to induce paradigm shifts (Yang, Deng, et al., 2023; Yang, Gong, et al., 2024; Yang, Hu, et al., 2023). A significant concern with the CD index is its distribution, which is highly centered around zero (Leibel & Bornmann, 2024; Yang, Gong, et al., 2024). To address this, we follow existing studies by setting a dummy variable, considering a paper to be disruptive when its CD index is above zero.

3.5 | Fixed effect regressions

To examine the relationship between team academic diversity, other team diversity characteristics, paper interdisciplinarity, and scientific disruption, we employ a series of regression models. To account for heterogeneity across scientific fields, temporal trends, research topics, publication venues, countries, and institutional affiliations, we incorporate five levels of fixed effects into our models. First, we introduce field fixed effects F_f, accounting for differences in team patterns across broad scientific categories. Specifically, $F_f = 1$ if the second-level field F_f is a subfield of a corresponding first-level field, as classified by MAG.

Second, we include year fixed effects Y_t, capturing fluctuations and trends over time by controlling for publication years, which range from 1970 to 2015.

Third, publication venue fixed effects V_v are incorporated to control for heterogeneity across outlets. These effects cover 39,893 distinct journals, addressing potential biases arising from differences in journal reputation or audience.

Fourth, we introduce country fixed effects C_c, controlling for the geographic location of the corresponding (last) author. This variable encompasses 202 countries, recognizing the potential influence of national academic systems and policies on team structures.

Finally, we introduce institutional tier fixed effects T_{Ins} to capture the impact of institutional prestige on

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team composition. Institutions are ranked by their h-index within the MAG dataset. Institutions are then grouped into four tiers: Tier 1 (T1) includes the top 1% of institutions, Tier 2 (T2) represents those ranked in the top 1%–5%, Tier 3 (T3) comprises institutions within the top 5%–20%, and Tier 4 (T4) includes all other institutions.

In addition to these fixed effects, we incorporate team size and its interaction with the dependent variables, as well as the average citation count of team members and its interaction with the dependent variables, to control for team composition effects.

We apply an ordinary least squares (OLS) regression model to estimate the impact of team academic diversity on the various outcome measures, with the exception of disruptive papers, for which we employ logistic regression. The OLS model is specified as follows:

$$DV_i = \alpha + \beta_1(\text{Academic diversity}_i) + \sum_{k=2}^{K}\beta_k(\text{Control}_{k,i}) + F_f + Y_t + V_v + C_c + T_{Ins} + \epsilon_i,$$

where i represents the article, t the year of publication, f the field, $\text{Control}_{k,i}$ represents the control variables, Y_t denotes year fixed effects, F_f captures second-level MAG field fixed effects, V_v captures publication venue fixed effects, C_C captures country fixed effects, ϵ_i denotes the error term and α denotes the constant term.

4 | DYNAMIC TREND AND DISTRIBUTIONS

4.1 | Temporal dynamics of academic diversity

We begin by examining the global trends in team academic diversity over time. As depicted in Figure 1b–d, academic diversity metrics, including academic entropy, academic standard deviation, and academic disparity, exhibit consistent growth across all fields—health and medicine, science and engineering, social sciences, and arts and humanities. Notably, we also observe an upward trend in average academic status over time (Figure 1a). To account for network dynamics, such as the total number of citations, we developed a null model to capture the expected academic values for each year. The results, presented in Figure 1e–h (in red), indicate that while the null model shows a rise in average academic status, it does not exhibit substantial growth in academic entropy, standard deviation, or disparity. Finally, by comparing the empirical data with the expected values from the null model (Figure 1i–l), we find that while the average academic status decreases relative to the null model, academic diversity metrics demonstrate a clear increase.

This growth suggests that over time, research teams are becoming more diverse in terms of disciplinary backgrounds. Interestingly, while average academic status also rises, the null model analysis reveals that this trend can largely be attributed to network dynamics, such as increasing citation numbers. The divergence between the empirical data and the null model suggests that the observed increase in academic diversity is not simply a byproduct of broader network effects but reflects a substantive shift toward more interdisciplinary collaboration. This underscores the importance of academic diversity as an independent and growing factor in research team composition. This rising diversity in team composition may have implications for the innovative capacity of research teams, a relationship we explore further in Section 5.

4.2 | Distributions across fields and regions

We analyze the distribution of academic diversity across 19 major scientific disciplines as classified by MAG, encompassing Medicine, Biology, Computer Science, Physics, Geology, Mathematics, Chemistry, Engineering, Geography, Materials Science, Environmental Science, Business, Political Science, Economics, Psychology, Sociology, History, Art, and Philosophy. As depicted in Figure 2b–d, the null model results are represented in gray, while the actual values are distinguished by colors corresponding to each disciplinary category. Most fields demonstrate a lower-than-expected academic entropy, with observed values falling below those predicted by the null model. However, disciplines such as Materials Science, Chemistry, Biology, and Medicine exhibit higher-than-expected academic entropy, indicating elevated levels of academic diversity and structural hierarchy. This suggests that these disciplines may possess more complex academic frameworks, characterized by a broader representation of diverse expertise and greater hierarchical depth relative to other fields.

We further investigate the regional distribution of academic diversity in science by analyzing the affiliation locations of the last authors, using this information to identify each country. For each region, we compute the difference between the observed and expected values from the null model (i.e., real − null values). Regions with positive differences (real − null >0) are highlighted in orange, indicating overrepresented academic diversity,

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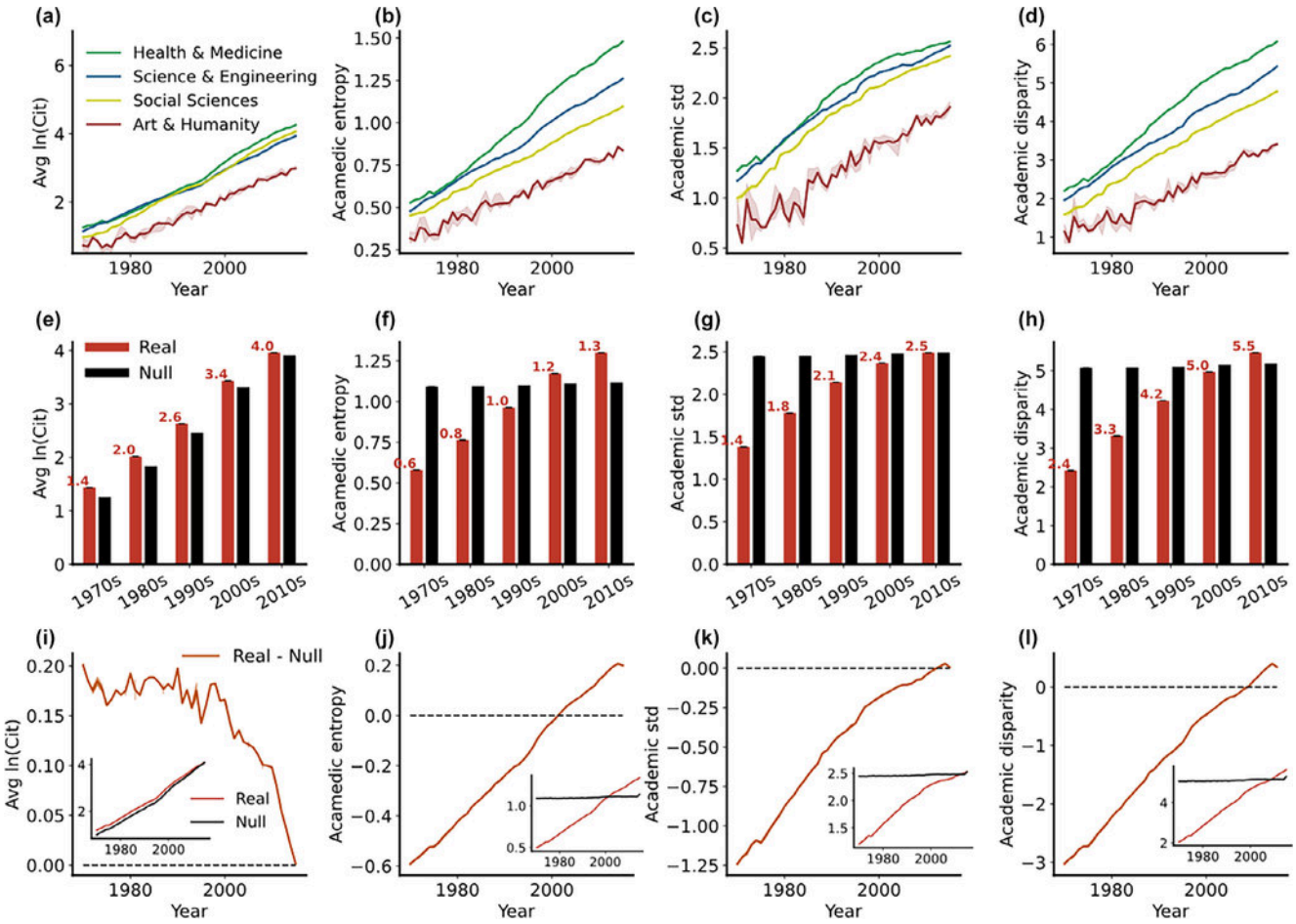


FIGURE 1 Temporal evolution of academic diversity in scientific teams (1970–2015). Panels (a–d) show the steady increase over time in various measures of academic diversity across different fields, including health and medicine, science and engineering, social sciences, and arts and humanities: (a) the average academic status of teams, based on dynamic citation counts, (b) academic entropy within teams, (c) academic standard deviation, and (d) academic disparity among team members. We include a null model that randomly reshuffles author-paper links while preserving the distribution of years and fields. Both the real data and the null model exhibit an increasing trend in the average academic status of team members from 1970 to 2015 (e). However, while the real data show increasing trends in academic entropy, standard deviation, and disparity, the null model does not display such trends (f-h). Additionally, we report real-minus-null results, highlighting trends adjusted for network factors. These show a decrease in the average academic status of team members over time (i), while measures of academic diversity, including entropy, standard deviation, and disparity, increase (j–l).

while regions with negative differences (real − null <0) are shaded in gray, signifying underrepresentation. The results in Figure 2e,f reveal that most developed regions, such as the United States, Europe, and Japan, exhibit overrepresented academic diversity, with real − null differences consistently above zero. In contrast, many developing regions, including parts of Africa and South America, show underrepresented academic diversity, with real − null differences predominantly below zero. This suggests a significant disparity in the distribution of academic diversity across regions, with developed countries displaying a stronger presence in diverse academic contributions compared to their developing counterparts.

5 | RELATIONSHIP WITH EXISTING MEASURES

5.1 | Other team diversity measures

We examine the relationships between the proposed metrics for team academic diversity and established characteristics of team diversity, including team age, nationality, academic discipline, and gender composition. Specifically, we quantify team age entropy, internationalism, field entropy, and gender entropy while investigating their field-level associations with academic diversity. We compute average values for the academic diversity metrics—namely academic entropy, academic standard deviation,

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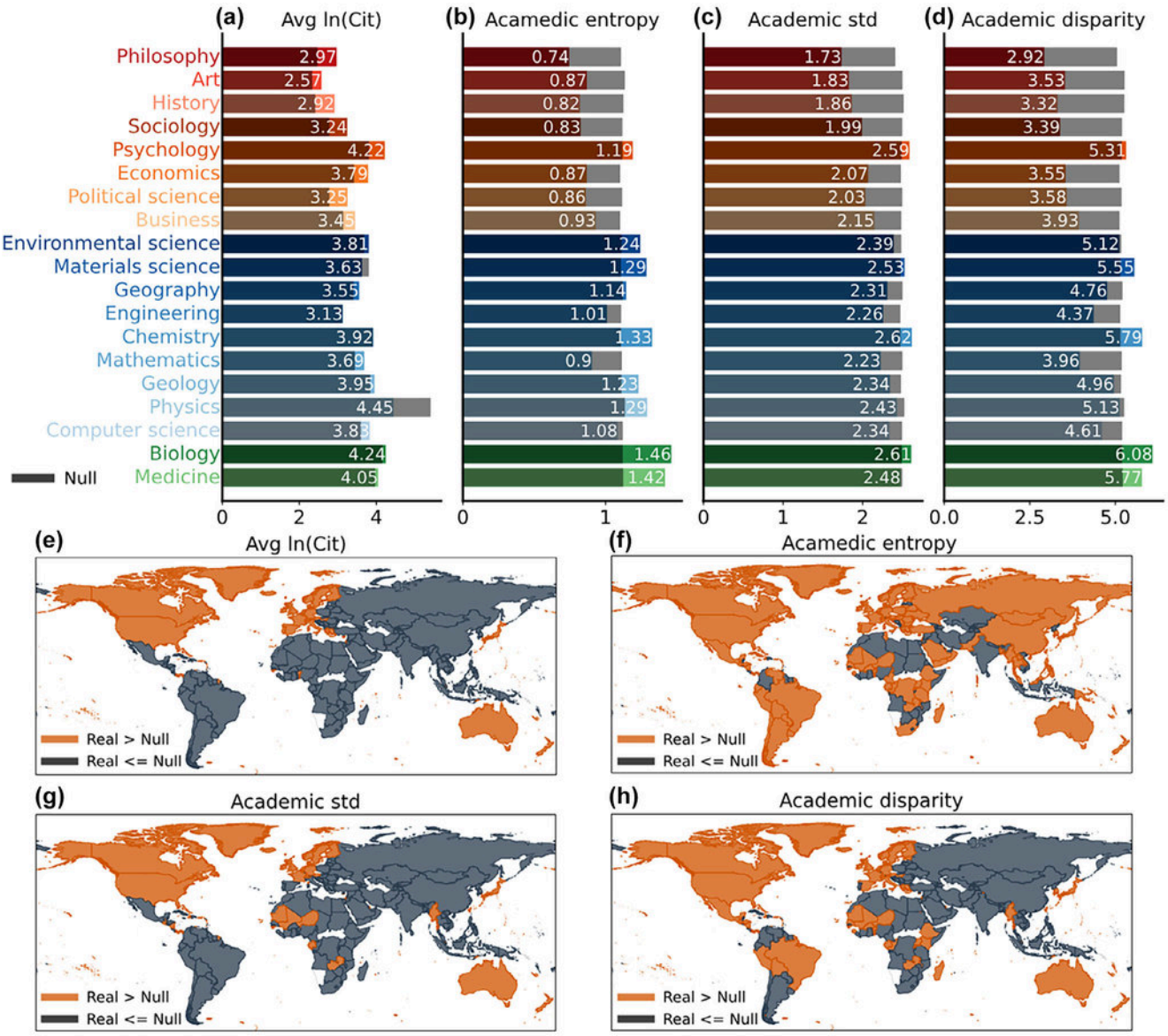


FIGURE 2 Distributions of academic diversity in scientific teams across fields and regions (2010s). Panels (a–d) display the average values of various academic diversity measures across 19 MAG 1st-level fields: (a) average academic status of teams, based on dynamic citation counts, (b) academic entropy within teams, (c) academic standard deviation, and (d) academic disparity among team members. Panels (e–h) show the average values of these academic diversity measures across different countries, based on the last authors affiliation locations. A null model, represented in gray, randomly reshuffles author-paper links. Fields or regions where the real academic diversity exceeds the null model are considered to have overrepresented academic diversity, whereas fields or regions with lower values compared to the null model indicate underrepresented academic diversity.

and academic disparity—alongside team-specific measures such as team age entropy, internationalism, field entropy, and gender entropy across 292 second-level fields in MAG.

Our findings, illustrated in Figure 3, reveal that all metrics of team academic diversity demonstrate positive correlations with team age entropy, internationalism, field entropy, and gender entropy at the field level. Notably, the Pearson correlation coefficient between team academic entropy and team age entropy is particularly robust. This pronounced relationship suggests that teams exhibiting greater academic age tend to possess higher academic status, at least at the aggregate level.

We further examine the paper-level relationships, specifically the estimated effects of academic entropy on team characteristics. We employ a series of OLS regression models to assess these relationships. In Figure 4, Model 1 (and its variants) serves as a baseline without control variables. In Model 2 (and its variants), we

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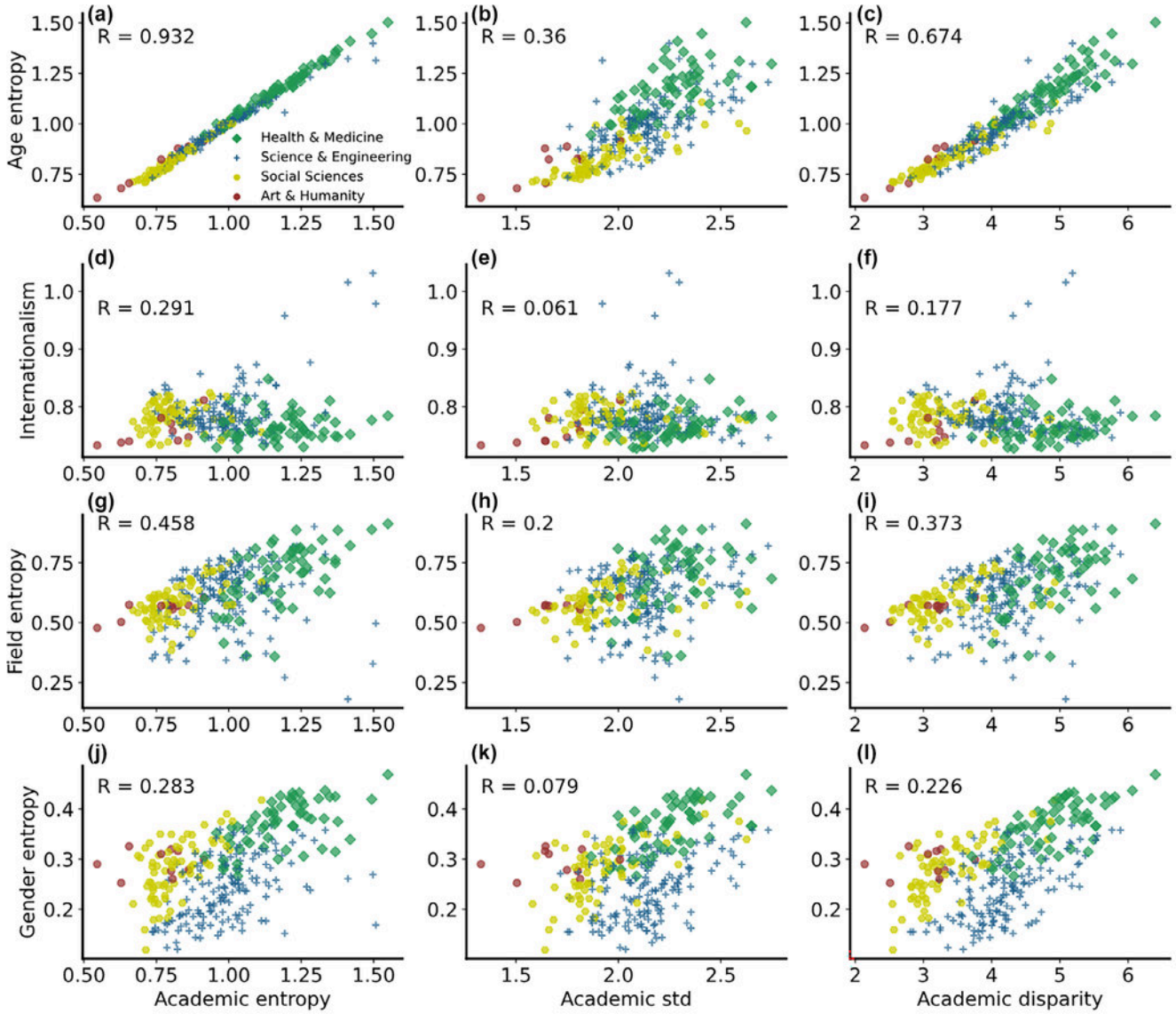


FIGURE 3 Field-level correlations between academic diversity measures and other team characteristics. Panels (a–c) depict the relationships and Pearson correlation coefficients (R) between academic diversity measures—academic entropy, academic standard deviation, and academic disparity—and team age entropy across fields. Panels (d–f) show the relationships and Pearson R values between academic diversity measures and team internationalism. Panels (g–i) illustrate the relationships and Pearson R values between academic diversity measures and team field entropy, while panels (j–l) focus on the relationships between academic diversity measures and team gender entropy. Each node represents the average values for all papers within a given field (292 MAG 2nd-level fields), with node colors indicating the top-level field classification.

introduce fixed effects for year, field, journal, country, and institution tier. Model 3 (and its variants) adds team size along with its interaction with academic entropy, while Model 4 (and its variants) further incorporates average citations of team members and their interaction with academic entropy.

The results reveal a consistent and significant positive association between academic entropy and team age entropy, internationalism, team field entropy, and team gender entropy at the 0.001 significance level across all models, with the exception of Models 7 and 8. Notably, in these latter models, controlling for team size reveals a negative relationship with internationalism. Additionally, we identify a negative mediating effect of team size; specifically, its interaction with academic entropy yields significantly negative coefficients, indicating that smaller teams exhibit a stronger positive relationship between academic entropy and other team diversity measures. The consistent positive associations between academic diversity measures and team age entropy, internationalism, field entropy, and gender entropy highlight the importance of diverse academic backgrounds and experiences in enhancing team dynamics.

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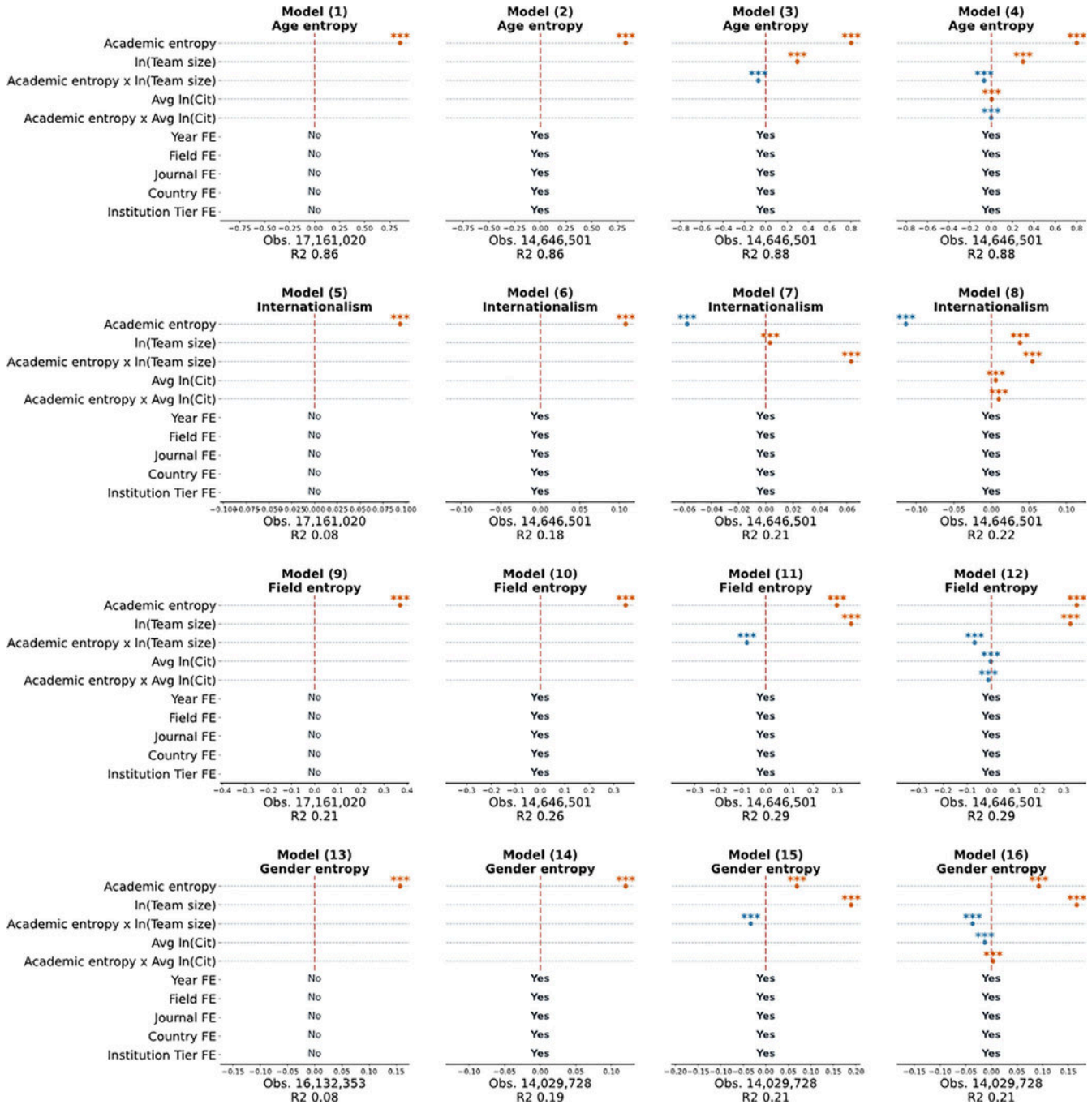


FIGURE 4 Paper-level estimated effects of academic entropy on team characteristics (age entropy, internationalism, field entropy, and gender entropy) using OLS regressions. The figure presents estimated effect sizes (nodes), 95% confidence intervals (bars) based on robust standard errors, and significance levels (stars) for both the independent variable (academic entropy) and control variables. Observations and R^2 values are also reported. Orange nodes represent positive effects, while blue nodes indicate negative effects. Significance levels are denoted by $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$. Model (1) includes no controls. Model (2) introduces fixed effects for year, field, journal, country, and institution tier. Model (3) adds team size and its interaction with academic entropy, and Model (4) further incorporates average team member citations and their interaction with academic entropy.

5.2 | Paper interdisciplinarity

We then evaluate the proposed team academic diversity metrics and investigate their relationship with established measures of paper interdisciplinarity, including interdisciplinary entropy, variety, disparity, and the Rao-Stirling index. Our analysis focuses on the field-level association between these diversity metrics and interdisciplinarity. Specifically, we calculate the average values of academic diversity metrics—such as academic entropy,

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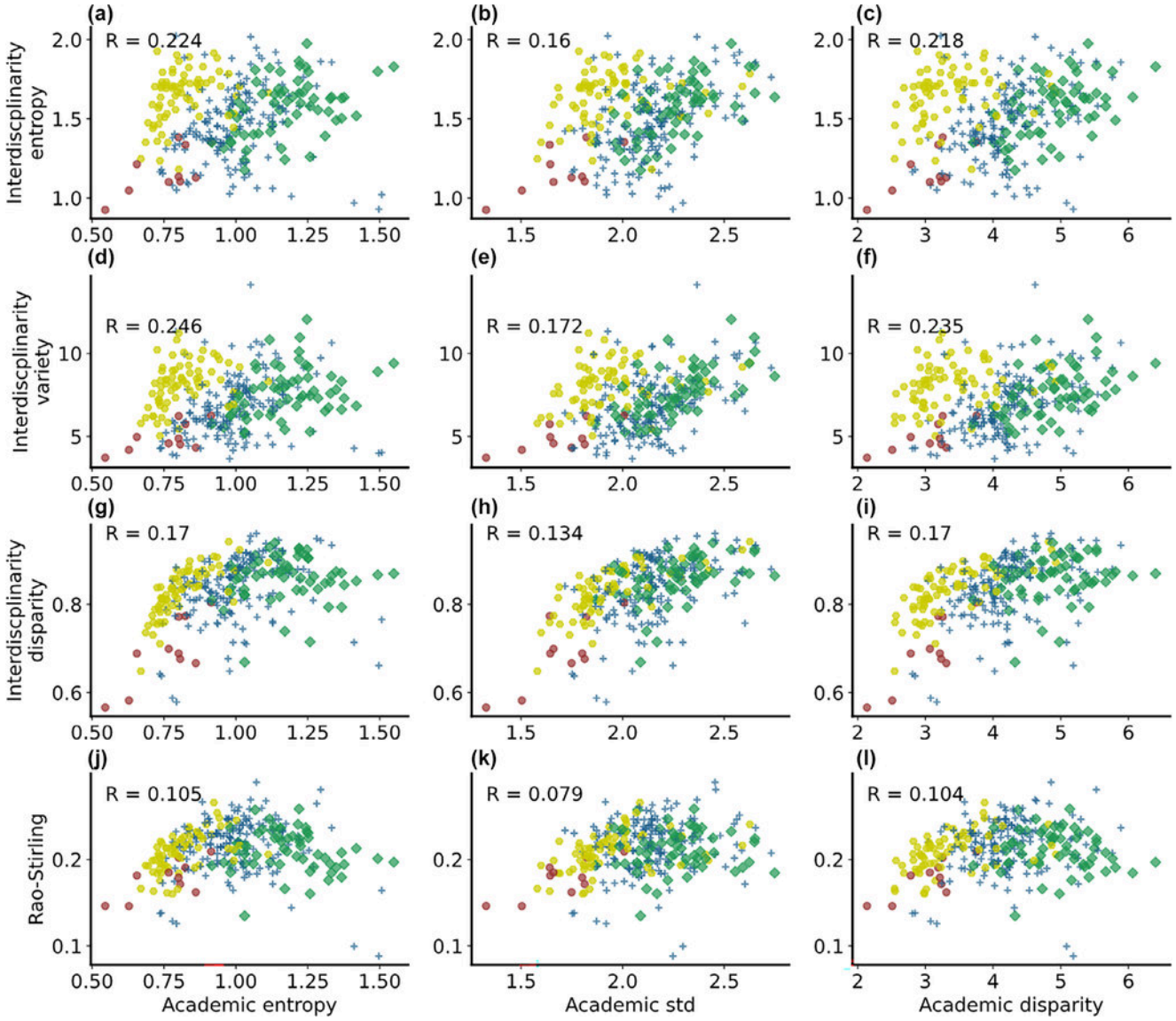


FIGURE 5 Field-level correlations between academic diversity measures and paper interdisciplinarity measures. Panels (a–c) depict the relationships and Pearson correlation coefficients (R) between academic diversity measures (academic entropy, academic standard deviation, and academic disparity) and interdisciplinary entropy across fields. Panels (d–f) show the relationships and Pearson R values between academic diversity measures and interdisciplinary variety. Panels (g–i) illustrate the relationships and Pearson R values between academic diversity measures and interdisciplinary disparity, while panels (j–l) focus on the relationships between academic diversity measures and Rao–Stirling. Each node represents the average values for all papers within a given field (292 MAG 2nd-level fields), with node colors indicating the top-level field classification.

standard deviation, and disparity—alongside interdisciplinarity measures across 292 second-level fields.

The results, summarized in Figure 5, demonstrate a positive correlation between all team academic diversity metrics and interdisciplinarity measures, including interdisciplinary entropy, variety, disparity, and the Rao-Stirling index at the field level. Nonetheless, the Pearson correlation coefficients indicate relatively weak associations between team academic entropy and the interdisciplinarity measures.

We extend our analysis to examine paper-level relationships, focusing on the estimated effects of academic entropy on interdisciplinarity measures. To assess these relationships, we implement a series of regression models. In Figure 6, Model 1 (and its variants) serves as a baseline specification without control variables. In Model 2 (and its variants), we introduce fixed effects for year, field, journal, country, and institution tier. Model 3 (and its variants) includes team size and its interaction with academic entropy, while Model 4 (and its variants) incorporates additional controls for average citations of team members, along with their interaction with academic entropy.

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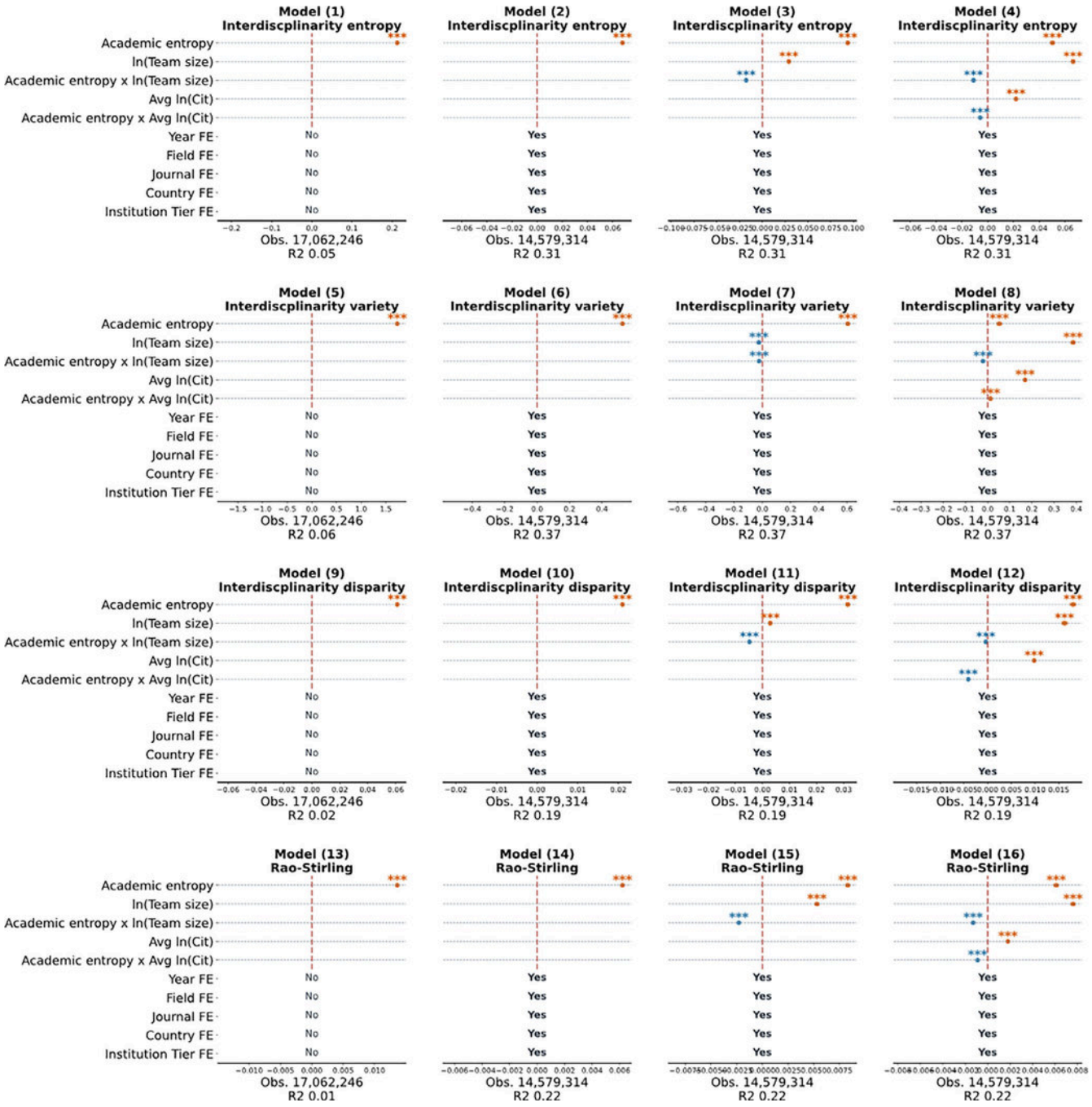


FIGURE 6 Paper-level estimated effects of academic entropy on paper interdisciplinarity measures (interdisciplinary entropy, interdisciplinary variety, interdisciplinary disparity and Rao-Stirling) using OLS regressions. The figure presents estimated effect sizes (nodes), 95% confidence intervals (bars) based on robust standard errors, and significance levels (stars) for both the independent variable (academic entropy) and control variables. Observations and R^2 values are also reported. Orange nodes represent positive effects, while blue nodes indicate negative effects. Significance levels are denoted by $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$. Model (1) includes no controls. Model (2) introduces fixed effects for year, field, journal, country, and institution tier. Model (3) adds team size and its interaction with academic entropy, and Model (4) further incorporates average team member citations and their interaction with academic entropy.

The results consistently demonstrate a significant positive association between academic entropy and all interdisciplinarity measures—interdisciplinary entropy, variety, disparity, and the Rao-Stirling index—across all models, with significance at the 0.001 level. Furthermore, we observe a negative moderating effect of team size; specifically, the interaction between team size and academic entropy yields significantly negative coefficients, suggesting that smaller teams display a stronger positive relationship between academic entropy and interdisciplinarity.

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5.3 | Scientific disruption

The CD index, grounded in an analysis of structural features within the deep citation network, provides a systematic framework for assessing the disruptive potential of academic papers. This index quantifies the alignment of a paper with established knowledge while also measuring its capacity to catalyze paradigm shifts. We examine the relationship between proposed metrics of academic diversity within research teams and the incidence of scientific disruption. Specifically, we classify papers with a CD index greater than zero as disruptive. As shown in Figure 7a–c, at an aggregated field level, we find that metrics such as academic entropy, academic standard deviation, and academic disparity exhibit a negative correlation with the probability of disruptive papers. This suggests that fields characterized by higher academic diversity are more prone to consolidate existing knowledge, whereas those with lower diversity are more likely to experience disruption.

Further, we analyze the paper-level relationships to provide a more intuitive understanding. By stratifying academic entropy, standard deviation, and disparity into deciles, we calculate the average probability of disruptive papers within each decile, as illustrated in Figure 7d–f. Our findings consistently demonstrate that greater academic diversity correlates with a reduced probability of disruptive contributions. Notably, the transition from the first to the second decile in academic diversity metrics corresponds to an approximate 8% decrease in the likelihood of identifying disruptive papers.

We subsequently investigate the estimated effects of academic entropy on the probability of disruptive papers using logistic regression analysis. A series of regression models is employed to elucidate these relationships. As shown in Figure 8, we establish a baseline specification devoid of control variables in Model 1. Model 2 introduces fixed effects for year, field, journal, country, and institution tier. Model 3 incorporates team size and its interaction with academic entropy, while Model 4 further accounts for the average citations of team members and their interaction with academic entropy.

The findings consistently reveal a significant negative association between academic entropy and the likelihood of disruptive papers across all models. This suggests that higher levels of academic entropy tend to inhibit the generation of disruptive contributions. This finding aligns with the notion that while diversity can foster creativity, it may also lead to the consolidation of existing paradigms rather than the emergence of innovative breakthroughs.

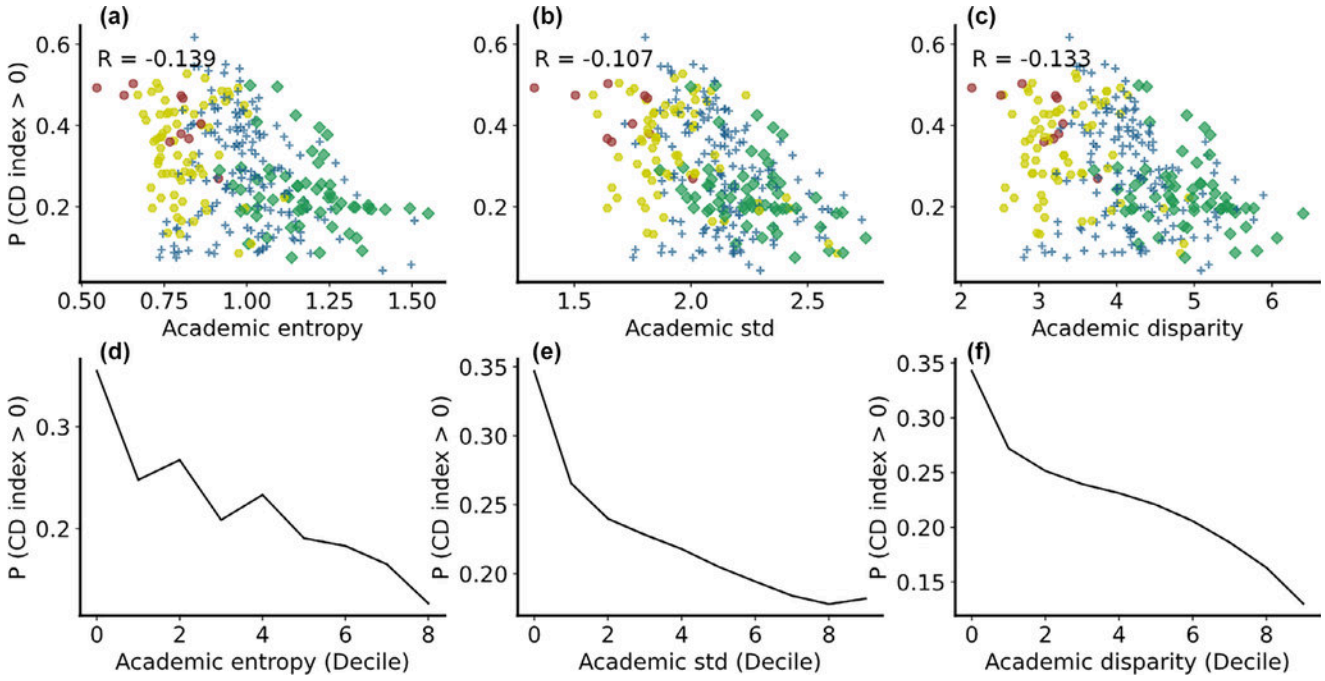


FIGURE 7 The relationship between academic diversity and scientific disruption. Panels (a–c) illustrate the field-level relationships and Pearson correlation coefficients between academic diversity measures—academic entropy, academic standard deviation, and academic disparity—and the likelihood of producing disruptive papers (CD index >0) across fields. Each node represents the average values for all papers within a given field (292 MAG 2nd-level fields), with node colors corresponding to the top-level field classification. Panels (d–f) show the relationship between academic diversity measures and the probability of disruptive papers (CD index >0). The results suggest a negative association between academic diversity and scientific disruption.

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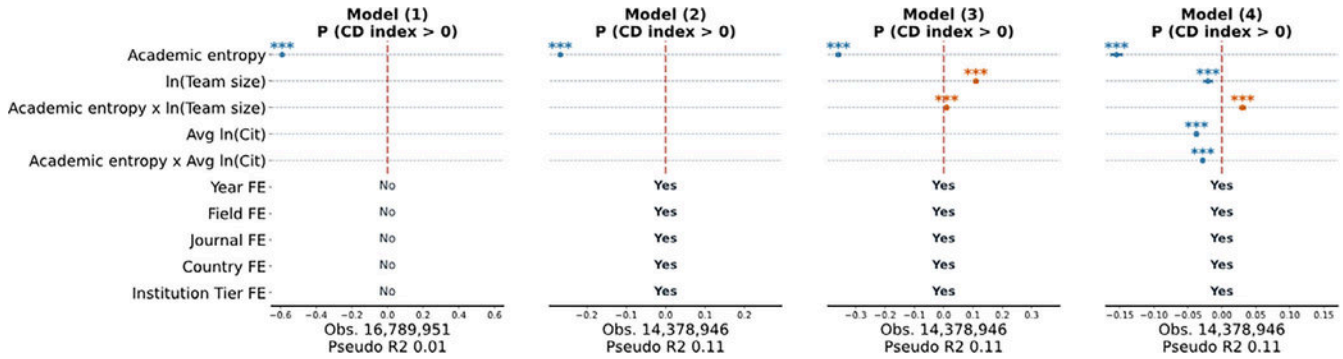


FIGURE 8 Paper-level estimated effects of academic entropy on the probability of disruptive papers using logistic regressions. The figure presents estimated effect sizes (nodes), 95% confidence intervals (bars) based on robust standard errors, and significance levels (stars) for both the independent variable (academic entropy) and control variables. Observations and Pseudo R^2 values are also reported. Orange nodes represent positive effects, while blue nodes indicate negative effects. Significance levels are denoted by $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$. Model (1) includes no controls. Model (2) introduces fixed effects for year, field, journal, country, and institution tier. Model (3) adds team size and its interaction with academic entropy, and Model (4) further incorporates average team member citations and their interaction with academic entropy.

Additionally, we identify a positive moderating effect of team size; specifically, the interaction term between team size and academic entropy produces significantly positive coefficients, indicating that larger teams exhibit a more pronounced negative relationship between academic entropy and the probability of producing disruptive contributions.

6 | DISCUSSION

This study contributes to the literature on team diversity, interdisciplinarity, and scientific innovation by introducing academic diversity as a distinct and influential factor in the composition and performance of research teams. Our findings provide new insights into the associations between academic diversity and scientific outcomes, advancing theories in the science of science, particularly regarding team composition and its relationships with knowledge production and disruption.

We extend the understanding of team diversity beyond traditional dimensions—such as gender, age, and nationality (Hsiehchen et al., 2015; Lin et al., 2023; Liu et al., 2024)—by presenting academic diversity as a measurable attribute reflecting the range of academic experiences and fields within a team. Our results indicate that higher academic diversity positively correlates with team interdisciplinarity but negatively correlates with scientific disruption. This challenges existing theories that posit diversity as a uniformly positive driver of innovation, suggesting instead that diversity is associated with greater interdisciplinary integration (Yang, 2025b), yet may be linked to knowledge consolidation rather than disruptive breakthroughs (Wu et al., 2019).

The practical implications of this study are significant for funding agencies and policymakers seeking to optimize team composition for scientific output and innovation. The steady rise in academic diversity over time, as evidenced by increasing metrics like academic entropy, standard deviation, and disparity, suggests trends in the structure of scientific collaboration. This trend indicates that academic teams are increasingly stratified in terms of expertise and recognition, reflecting a growing academic hierarchy within research teams. Higher diversity in academic status is associated with teams that include both highly established scholars and less experienced researchers, which may be linked to power imbalances in decision-making and credit distribution. While this hierarchical structure is associated with incremental innovation through the consolidation of diverse expertise, it is also correlated with a lower likelihood of disruptive scientific breakthroughs, as teams may be more inclined to build upon existing knowledge rather than challenge prevailing paradigms. Furthermore, the disparity in academic diversity across regions, with developed countries showing overrepresentation, suggests potential global inequities in research opportunities, which may be associated with limited participation and contribution from researchers in underrepresented regions. These findings highlight the need for policies that balance the benefits of diversity with the challenges of hierarchical structures, ensuring that diverse teams can contribute to both incremental and transformative scientific advances.

Our findings offer insights into structuring teams to achieve specific research goals, whether related to interdisciplinary collaboration or disruptive innovation. Teams addressing complex, multifaceted problems may show stronger associations with varied academic backgrounds. Funding agencies and institutional leaders could consider supporting teams with high academic diversity when the

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objective is to promote cross-disciplinary collaboration, potentially adjusting grant selection criteria to prioritize such formations, particularly in fields like climate science, public health, and AI research. Conversely, institutions aiming to produce disruptive science may need to reconsider the emphasis placed on diversity in team composition. While academic diversity is associated with knowledge integration, teams focused on groundbreaking research may show stronger associations with a more homogeneous composition, which is linked to deeper exploration of novel, high-risk ideas. Our findings suggest that smaller teams may exhibit a stronger relationship between academic diversity and disruptive research, supporting the creation of agile, smaller research teams for high-risk, high-reward projects. Funding agencies could also allocate specific grants for these smaller, interdisciplinary teams that aim to push the boundaries of existing knowledge.

Despite these contributions, this study has several limitations. While citations are a widely accepted proxy for academic status and impact, they can be influenced by publication practices, field-specific norms, and the temporal dynamics of citation accumulation, which may introduce biases into our findings. The extensive dataset spanning 292 scientific disciplines complicates direct comparisons due to variations in research practices and citation behaviors. Additionally, our correlational analysis limits the ability to draw causal inferences regarding the relationships between academic diversity and scientific innovation. Although we introduce new metrics for assessing academic diversity, these measures may not fully capture all dimensions of diversity, such as interdisciplinary collaboration or individual contributions. Unobserved confounding variables, including institutional reputation and funding levels, may also be associated with the observed relationships. Furthermore, our focus on team-level analysis neglects individual-level variations that may be linked to research outcomes. The temporal scope of the dataset may limit the relevance of findings due to shifts in academic practices over time. Lastly, while the dataset includes outputs from multiple countries, regional disparities in funding and research culture may be associated with the results, necessitating further investigation into the interplay between geographical factors and academic diversity.

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CONFLICT OF INTEREST STATEMENT

The author declares no competing interest relevant to this article.

DATA AVAILABILITY STATEMENT

The MAG data can be downloaded via https://zenodo.org/record/2628216#.Y-7RR_5Bz-g. Other data used in this study can be obtained by making reasonable requests.

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