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Delayed citation impact of interdisciplinary research

Yang Zhang [a], Yang Wang [a,*], Haifeng Du [a], Shlomo Havlin [b]

[a] *School of Public Policy and Administration, Xi'an Jiaotong University, Xi'an 710049, China*
[b] *Department of Physics, Bar-Ilan University, Ramat-Gan 52900, Israel*

A R T I C L E I N F O

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A B S T R A C T

Interdisciplinary research increasingly fuels innovation, and is a key input for future breakthroughs. Yet the timing of when interdisciplinary research achieves its highest citation impact remains unclear. Here, we use the time of a paper to reach its citation peak to quantify citation dynamics, and examine its relationship with paper interdisciplinarity. Using large scale publication datasets spanning over 37 years, our results suggest that interdisciplinary papers show significant delayed citation impact both at the individual paper level and collectively, as it takes longer for highly interdisciplinary papers to reach their citation peak as well as their half citations. Such relationships are nearly universal across various scientific disciplines and time periods. Furthermore, we study the underlying forces behind this delayed impact, finding that the effect goes beyond the Matthew effect (i.e., the rich-get-richer effect). Although team size and content conventionality are partly related to the citation delay, they cannot fully explain this effect. Overall, our results suggest that governments, research administrators, and funding agencies should be aware of this general feature of interdisciplinary science, which may have broad policy implications.

1. Introduction

In recent years, there have been numerous calls to foster interdisciplinary research (Brown, Deletic, & Wong, 2015; Bu, Ding, Liang, & Murray, 2018a; Jacobs & Frickel, 2009; Jones, Wuchty, & Uzzi, 2008; Visholm, Grosen, Norn, & Jensen, 2012; Wang & Barabási, 2021; Zeng et al., 2017), as advocates suggest that interdisciplinary science can solve complex societal problems that individual disciplines cannot address alone (Jacobs & Frickel, 2009; Klein, 1990). The Human Genome Project, for example, assembled scientists from various scientific disciplines, including engineering, biology, computer science, among other, which facilitated the unravelling of molecular mechanisms underlying many diseases, and brought about revolutions in cancer diagnosis and treatment (Green, Watson, & Collins, 2015). As Nobel laureate Robert J. Shiller wrote, "*More creative solutions tend to come from imaginative interdisciplinary collaboration*". Although empirical investigations suggest that highly interdisciplinary research may receive broader and more citations compared to less interdisciplinary research (Chen, Arsenault, & Larivière, 2015, 2022; Garfield, 1964; Gates, Ke, Varol, & Barabási, 2019; Ke, 2020; Levitt & Thelwall, 2009; Rinia, Van Leeuwen, Bruins, Van Vuren & Van Raan, 2001a; Rogers, 2003; Steele & Stier, 2000; Wang, Thijs, & Glänzel, 2015; Zhang, Sun, Jiang, & Huang, 2021), studies focusing on specific fields or individual countries indicate that interdisciplinary research faces numerous barriers (Rinia, Van Leeuwen, Van Vuren, & Van Raan, 2001b). These barriers encompass aspects such as securing scientific funding (Bromham, Dinnage, & Hua, 2016; Ledford, 2015), establishing research centers

* Corresponding author.
E-mail address: yang.wang@xjtu.edu.cn (Y. Wang).

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(Ledford, 2015), and obtaining prestigious prizes (Bromham et al., 2016; Jacobs & Frickel, 2009; Ledford, 2015; Szell, Ma, & Sinatra, 2018). Rarely have these barriers been the subject of large-scale empirical investigations, and the scientific community's understanding of when major impacts occur for interdisciplinary research, and why such barriers exist is remarkably limited. Understanding these questions is crucial for addressing a wide array of issues in science, from training junior scientists to supporting interdisciplinary research (Van Noorden, 2015).

The availability of large-scale datasets and advanced computational tools have enabled the quantitative understanding of the impact of interdisciplinary research (Bromham et al., 2016; Bu et al., 2018b; Jacobs & Frickel, 2009; Levitt & Thelwall, 2008; Leydesdorff, Wagner, & Bornmann, 2019; Szell et al., 2018; Wang et al., 2015). Indeed, earlier studies found negative correlations between paper interdisciplinarity and its short-term citations, using limited data from specific years (Chen et al., 2022; Wang et al., 2015). Additionally, papers that were not initially recognized often have the potential to gain citations through discoveries in other disciplines (Ke, Ferrara, Radicchi, & Flammini, 2015). These perspectives suggest a possible early citation penalty for interdisciplinary research. Yet at the same time, other observations indicate that such effects may not exist. For example, interdisciplinary research has been shown to exhibit a citation advantage regardless of time since publication (Zhang et al., 2021). It is also argued that multidisciplinary papers tend to attract citations more quickly than those in traditional disciplines (Wang, 2013). These contradictory opinions suggest that the temporal impact profile of interdisciplinary research remains unclear. Given the relevance of this question for funding agencies, individual researchers, scientific collaborations, as well as the institutions that support them, and building on recent scientific progress in the field of science of science (Liu et al., 2018; Ma, Mukherjee, & Uzzi, 2020; Azoulay, 2018; Fortunato, 2018; Uzzi, Mukherjee, Stringer, & Jones, 2013; Wang & Barabási, 2021; Wang, Song, & Barabási, 2013; Wang, Jones, & Wang, 2019; Yin, Wang, Evans, & Wang, 2019; Zeng et al., 2019, 2017), here we ask: does interdisciplinary research exhibit delayed citation impact? If so, what are the possible underlying mechanisms? How to quantify epistemic barriers impeding interdisciplinary research, including content conventionality and knowledge diffusion across disciplines?

In this study, we mainly use the Microsoft Academic Graph (MAG) dataset (Sinha et al., 2015), which comprises over 200 million digital publications spanning more than a century. We extract publication date, scientific fields, journal, authors, affiliations, citations and references for each paper. In this paper, we mainly focus on journal articles published between 1970 and 2007 to examine long-term citation dynamics. Within this timeframe, our sample contains 16,548,023 journal articles (see Supplementary Material S1 for additional sample details). Our study shows that papers with higher levels of interdisciplinarity, on average, take longer time to reach their citation peak. Furthermore, this effect is even more pronounced for papers with the most delayed citation peaks. Moreover, we observe that highly interdisciplinary research achieves significantly higher citation peaks compared to less interdisciplinary research. We find also that for a given period of time, highly interdisciplinary papers reach their half citations later. Our results also suggest that highly interdisciplinary research published in prestigious journals, authored by prominent researchers, and affiliated with prestigious institutions still exhibits this delayed citation impact, indicating that such effect is independent of reputations. Finally, our results suggest that neither team size nor content conventionality can fully account for this delay. Using large-scale data, our findings quantify when interdisciplinary research achieve its highest citation impact compared to regular papers across various scientific domains, and call for the need for suitable science policies.

2. Materials and methods

2.1. Data

Our primary data source for this paper is the Microsoft Academic Graph (MAG) database. To study the association between interdisciplinarity and the time to reach the citation peak, we extract, from the MAG data, each paper's publication date, scientific fields, references, forward citations, publication venues, authors, and institutions. We mainly focus on journal articles published between 1970 and 2007 to ensure sufficient citation window length. We specifically select papers with at least one reference, ending up with a final sample of 16,548,023 papers. The scientific field information in the MAG dataset is organized into a five-level hierarchical tree, with each field representing a specific scientific discipline or topic. Here, in order to measure a paper's interdisciplinarity based on the scientific fields of its reference list, we consider the 295 level-1 fields to which each reference in our sample belongs. These 295 level-1 fields are categorized into 19 level-0 scientific disciplines, and the first appearance of all 295 scientific fields within our dataset is before 1970. For instance, fields like data science, artificial intelligence, and machine learning (level-1 fields) all belong to "computer science" (level-0 field). Additionally, we provide the distribution of papers for each level-0 field in Fig. S1, which guides our primary analysis of the top four level-0 fields (i.e., medicine, chemistry, biology and physics) in the main text. While the MAG dataset has been retired after 2021, it is crucial to clarify that our primary dataset primarily consists of journal articles published before 2007, and we trace their citations up to the end of 2020. Therefore, the discontinuation of the MAG dataset after 2021 does not compromise the integrity of our core database.

Recent studies have offered systematic comparisons between various large-scale bibliometric datasets. In a prior study of Hug et al. (Hug & Brändle, 2017), the authors demonstrated that MAG exhibited superior coverage of journal articles compared to Web of Science, particularly when compared to a verified publication list from a university. They noted that citation analyses based on MAG, Scopus, and Web of Science yielded highly similar results, with correlation coefficients for paper citations hovering around 0.90. A recent study by Martín-Martín et al. observed that MAG had a larger number of publications compared to Scopus and Web of Science (WoS), with a notable ability to index publications in Humanities, Social Sciences, and Business, Economics & Management (Martín-Martín, Thelwall, Orduna-Malea, & Delgado López-Cózar, 2021). Additionally, earlier studies have indicated that MAG can effectively identify earlier versions of papers by merging preprints with their subsequent in-press versions (Thelwall, 2018). In a comprehensive comparison by Visser et al. that encompassed WoS, Scopus, Dimensions, Microsoft Academic Graph, and CrossRef, with matching of the complete document collection in each source, Microsoft Academic Graph emerged as the dataset with the most extensive overall coverage and the highest overlap with Scopus documents in comparison to Web of Science and Dimensions (Visser, Van Eck, & Waltman, 2021). In conclusion, MAG metadata continues to stand out as one of the most comprehensive bibliometric datasets (Hug & Brändle, 2017; Martín-Martín et al., 2021). Indeed, recent research has frequently leveraged the MAG data to unveil underlying patterns in science (Li, Zhang, Zheng, Cranmer, & Clauset, 2022; Peng, Ke, Budak, Romero, & Ahn, 2021; Xu, Wu, & Evans, 2022; Zhu, Jin, Ma, & Xu, 2023).

To further test the robustness of our results, we incorporate another extensive bibliometric dataset, namely the Dimensions dataset, which encompasses 119 million digital publications. The Dimensions dataset employs a hierarchical tree system for the categorization of scientific disciplines, consisting of two hierarchical levels. At the first level, it encompasses 22 broad scientific fields, spanning diverse domains like economics, engineering, and physical sciences. These overarching domains are subsequently subcategorized into a range of subfields. In our analysis, we concentrate on articles published from 1980 to 2007 within this dataset. We specifically select articles that have at least two references, resulting in a final dataset encompassing 6,871,193 publications. For additional details, see Supplementary Material S1.

To access institutional prestige, we gather data from the U.S. News Best Global Universities Rankings. This ranking evaluates the academic performance and reputation of more than 1500 universities worldwide, offering available information for students who look for education abroad. The U.S. News ranking uses 13 weighted indicators to calculate university rankings, including reputations (25 %), bibliometric indicators (65 %), scientific excellence (10 %). For instance, bibliometric indicators include publications (10 %), percentage of total publications that are among the top 10 % of the most cited papers (10 %), etc. For our analysis, we manually cross-reference the U.S. News data with the MAG institution information, to obtain institutional rankings for our sample. In cases where an

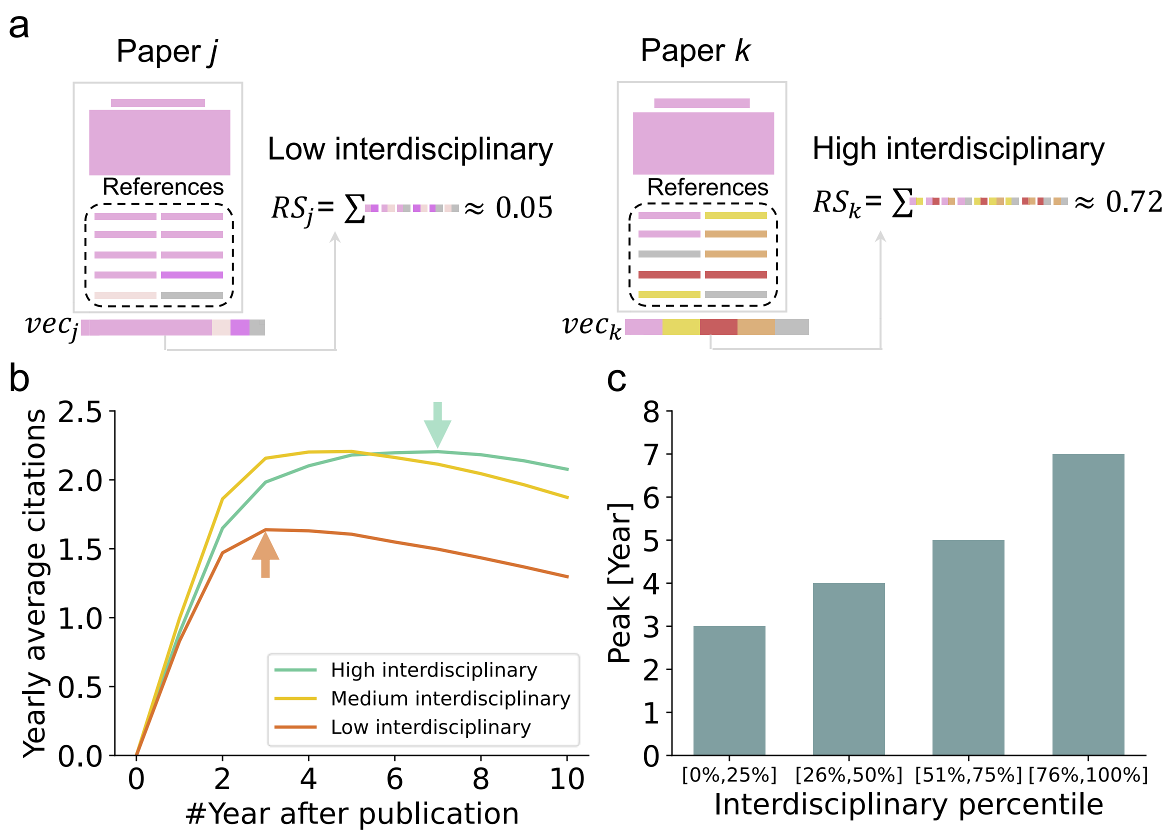

Fig. 1. Quantifying the interdisciplinary measure of scientific papers and its relationship with citation accumulation patterns. (a) An illustration of the interdisciplinary measure. The interdisciplinary measure quantifies how a paper is broadly inspired based on its reference list. Two papers could belong to the same scientific field, but absorb knowledge from several scientific fields with different distributions. An increasing value indicates broader inspiration integration, charactering with higher diversity of scientific fields in the reference list. (b) Yearly average citations of all papers, i.e., macroscopic view, within 10 years after publication for high, medium, and low interdisciplinary research. It reveals a systematic delayed citation accumulation pattern, particularly the year of the peak value, for high interdisciplinary research is significantly later compared to medium or low interdisciplinary research. (c) The peak time as a function of interdisciplinary percentile. We calculate the peak time using the curves of yearly average citations of all papers within 10 years after publication for research belonging to different interdisciplinary percentiles. The difference is statistically significant using bootstrapping (p-value <0.001). The error bars are not shown since they are too small. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

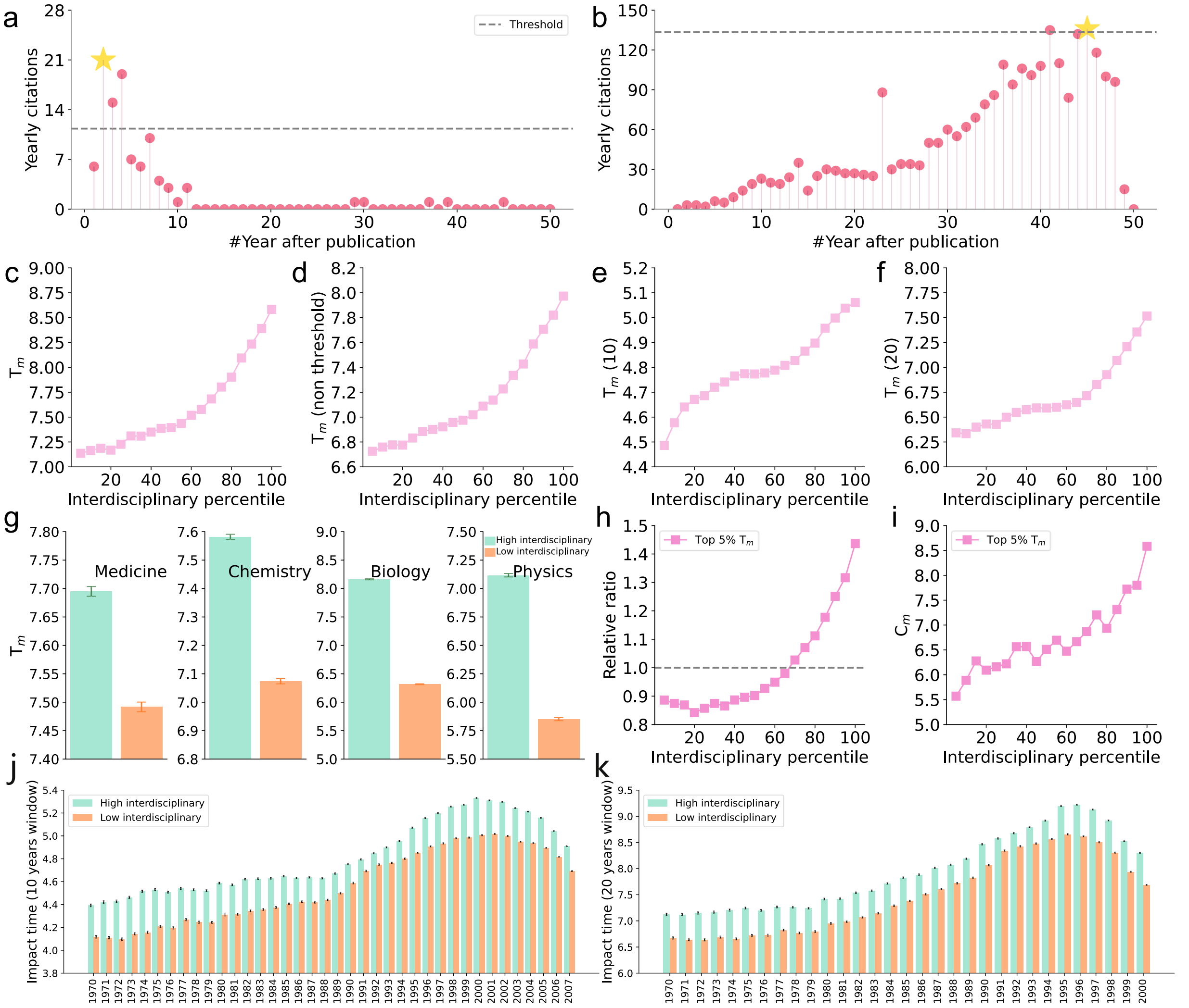

Fig. 2. Delayed citation impact of interdisciplinary research at the microscopic level of individual papers. (a, b) Illustration of T_m for individual papers. The yellow star represents the time when the papers reach their citation peak. Here, yearly citations need to exceed the threshold (average citations plus two standard deviations for all yearly citations of the focal paper, shown by the horizontal dashed line). We demonstrate (a) a paper with low interdisciplinary nature (i.e., *Rao-Stirling* diversity is 0.18) has $T_m = 2$, whereas the other paper (b) is of high interdisciplinary nature (i.e., *Rao-Stirling* diversity is 0.59) with $T_m = 45$. (c) For individual papers, the average T_m as a function of paper interdisciplinarity. Average T_m increases by 20 % from 7.1 years to 8.6 years as paper interdisciplinary level increases from the bottom 5 % to the top 5 %. (d) T_m(non threshold) is defined similarly to T_m, but without any specific citation threshold. (e) T_m(10) and (f) T_m(20) are defined similarly to T_m but exclusively considering 10-year and 20-year citation windows after the year of publication, respectively. (g) Comparing average T_m for high and low interdisciplinary research in the fields of medicine, chemistry, biology and physics with error bars representing standard errors. (h) The same as in (c) but for high T_m papers (in the top 5 % of T_m) rather than average behaviors. Relative ratios compare the observed fraction of papers of certain interdisciplinary levels with high T_m against the constant baseline of 5 %. We find only 4.4 % papers with high T_m are contributed by the bottom 5 % interdisciplinary papers and 7.2 % contributed by the top 5 % interdisciplinary papers. (i) For high T_m papers (papers with T_m in the top 5 %), average C_m (citations obtained at year T_m) as a function of interdisciplinary percentile. (j) Time to reach half citations as a function of time for high and low interdisciplinary papers, using 10-year citation windows. (k) The same as (j) but for 20-year citation windows. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

institution was not listed in the rankings, we labeled it as “no rank”.

2.2. *Quantifying paper’s interdisciplinarity*

A paper’s reference list reflects its sources of input knowledge, and citation relationships between papers characterize knowledge diffusion, enabling us to measure paper interdisciplinarity (Sun & Latora, 2020). To quantify the extent to which each study integrates previous wisdom, we employ the *Rao-Stirling* diversity (Gates et al., 2019; Ke, 2020; Stirling, 2007; Wang et al., 2015). In line with prior research, the procedure for calculating interdisciplinarity is as follows (Gates et al., 2019). For each paper d, we map each of its references α to a vector $\overrightarrow{r_\alpha^d} = (r_{\alpha,1}^d,\ r_{\alpha,2}^d, \ldots,\ r_{\alpha,k}^d)$ based on its scientific fields, where k is the number of fields in the MAG data (i.e., 295 level-1 fields). Thus the ith element of paper vector $\overrightarrow{a^d}$ is given by

$$a_i^d = \sum_{\alpha=1}^{n}\sum_{\beta=1}^{k}\frac{\delta\left(r_{\alpha,\beta}^d, i\right)}{k},$$

where δ is the characteristic function that equals 1 when $r_{\alpha,\beta}^d$ is the same as the ith scientific field, n is the total number of references and k is a set of scientific fields for a reference denoted by α. Moreover, we normalize each paper vector to obtain p_i at the ith element of individual paper vectors, which represents the normalized fraction of references a paper cite within field i. Next, we define the vector at the field level by aggregating paper vectors $\overrightarrow{a}$ over the set of articles that belong to the same field, i.e., $v_i = \sum_{d\in v_i}\overrightarrow{a^d}$, where V_i is all papers in field i. In general, as Fig. S2(A) shows, the distance between fields (i.e., 295 level-1 fields) within the same discipline (i.e., 19 level-0 fields) is smaller, suggesting that knowledge flow in the same discipline is more frequent than knowledge flow across distinct disciplines. For example, the knowledge combined between data science and statistics physics is more related to each other than the knowledge captured between nuclear physics and biochemistry. The distance between field i and field j is defined using the cosine similarity:

$$D_{ij} = 1 - \frac{v_i \cdot v_j}{\| v_i || \cdot \| v_j \|}.$$

Finally, for each paper d, we define its interdisciplinarity using the *Rao-Stirling* diversity:

$$RS_d = \sum_{i\neq j} D_{ij}p_ip_j,$$

where p_i and p_j represent respectively the fraction of paper d's references that belong to field i and j. The *Rao-Stirling* diversity thus obtains a small value if a paper draws on knowledge from similar disciplines (Fig. 1(a), left), and obtains a large value if a paper absorbs knowledge from various disciplines that are distant from each other (Fig. 1(a), right). Besides the *Rao-Stirling* diversity featured in the main text, we also utilize several other interdisciplinary measures (e.g., true diversity indicator (Leydesdorff et al., 2019; Zhang, Rousseau, & Glänzel, 2016), and *DIV* indicator (Leydesdorff et al., 2019) (see Supplementary Material S2 and Fig. S2).

2.3. Quantifying citation dynamics

Quantifying citation dynamics of individual papers requires determining the time when a paper gets cited since its publication. Firstly, we obtain the publication time (i.e., t_c) of all forward citations for each paper in our sample. Next, we calculate $\delta_t = t_c - t_d$ for each forward citation, where t_d captures the publication time of paper d and δ_t represents the time interval between the publication time of paper d and each forward citation time. After this, we get a per-year count of the number of citations for each paper. For example, the citation time window for papers published in 1970 is between 0 year and 50th year, where publication time is considered as 0 year, whereas the citation time window for papers published in 2007 is between 0 year and 13th year. As illustrated in Fig. 2(a), we quantify citation dynamics using T_m, which represents the time when the papers reach their citation peak. We also denote citations obtained at year T_m by C_m. To ensure significant citation peak for each paper, we only consider the peak that exceed the average yearly citations by more than two standard deviations.

We also harness several alternative methods to quantify citation dynamics. One is a mechanistic model proposed by Wang et.al., known as the WSB model (Wang et al., 2013) (see details in Supplementary Material S3). This model includes three fundamental ingredients, i.e., preferential attachment, aging and fitness. To be precise, preferential attachment captures the citation advantage of one article boosted by its previous cumulative citations; aging represents the impact decay as function of time; fitness is the popularity of one paper within its community, capturing the intrinsic value. In line with prior studies (He, Lei, & Wang, 2018; Shen, Wang, Song, & Barabási, 2014; Wang et al., 2013), we consider the citation dynamics of individual papers as a non-homogeneous Poisson process with the rate function:

$$x_d(t) = \ \lambda_d f_d(t;\mu_d,\ \sigma_d) i_d(t),$$

where $x_d(t)$ represents the citation rate function of paper d at time t, λ_d is the intrinsic fitness or attraction, $f_d(t;\mu_d,\ \sigma_d)$ is the relaxation function describing the long-term impact decay that follows a log-normal form,

$$f_d(t;\theta_d) = \ \frac{1}{\sqrt{2\pi}\sigma_d t}\exp(-\frac{(\ln t - u_d)^2}{2\sigma_d^2}\Bigg),$$

where u_d and σ_d characterize citation dynamics for individual papers, $i_d(t)$ is the cumulative citations the focal paper received till time t. u_d captures the time when paper d arrives at its citation peak point. The p-values of the fitting and direct visualizations of the fitting results are shown in Fig. S3. Following this model, we also directly calculate each paper's impact time, which is the time to reach its half total citations until a certain-year citation window.

Beyond the WSB model, it is well believed that a handful of articles attract substantial attentions many years after publication, and these kinds of articles cannot be captured by the WSB model, as most of such articles do not follow rise-and-fall citation dynamical pattern. To address this, we use the "sleeping beauty index (B index)" to quantify the citation dynamics of such awaken articles (Ke et al., 2015). The B index is determined by the duration of sleeping and the intensity of the awakening. More specifically, the awaken intensity represents the strength of suddenly receiving substantial attention from the situation where few citations occur during initial decades for one article. The B index of paper d with at least one citation is defined as follows,

$$B_d = \sum_{0}^{T_m} \frac{\frac{C_m - C_{t_0}}{T_m} \cdot t + C_{t_0} - C_t}{\max\{1, C_t\}},$$

where C_t is the number of citations at year t, C_{t_0} is the number of citations received by the paper in the year of its publication, C_m and T_m are the maximum number of citations and its corresponding year, respectively. Fig. S4 shows the graphical representation of calculating B index till time T_m.

2.4. Regression settings

To further eliminate the effects of the confounding factors, we employ ordinary least squares regressions to study the association between paper interdisciplinarity and citation dynamics. The regression model is shown as follows,

$$\mathrm{y}_d = \beta_i Inter_d + \beta_T \ln(T_d) + \beta_R \ln(R_d) + \beta_{af} A_{fd} + \beta_{al} A_{ld} + \beta_{aa} A_{ad} + \beta_{hf} H_{fd} + \beta_{hl} H_{ld} + \beta_{ha} H_{ad} + \sum_r \beta_r R_{rd} + \sum_j \beta_j J_d + \sum_y \beta_y Y_d + \sum_f \beta_f F_d + \epsilon_i.$$

The dependent variable y_d represents the time it takes for individual papers to reach the citation peak. Specifically, we use T_m in the main text, or u_d from the WSB model, or the B index. To ensure the robustness of our regression results, we also use the impact time, approximated as the characteristic year when an individual paper reaches half of its total citations after publication. The predictor of interest is interdisciplinarity, i.e., the *Rao-Stirling* diversity in the main text. To consolidate the robustness of the results, we also use alternative interdisciplinary indicators as described in Supplementary Material S2. To ensure that our results are not affected by other factors, we consider following variables as potential control variables: 1) T_d is team size. It measures the number of authors of a paper, and we transform the variable to its logarithm because of its fat-tail nature. 2) R_d is the number of references. We also convert this variable into its logarithmic form. 3) A_{fd} is the academic age of the first author. It measures the number of years from the first publication time till paper d's publication time. Academic age partly indicates an author's academic experience. 4) A_{ld} is the academic age of the last author. It measures the number of years from the first publication time till paper d's publication time. 5) A_{ad} is the average academic age of a team. It measures average number of years since the first publication till paper d's publication time over all team members. 6) H_{fd} is the h-index of the first author. It measures the impact of the first author till paper d's publication time. 7) H_{ld} is the h-index of the last author. It measures the impact of the last author till paper d's publication time. 8) H_{ad} is the average h-index of a team. It measures average impact of a team using the similar setting as H_{fd}. 9) R_{rd} is the fixed effect of the institution prestige as indicated by the U.S. News Ranking. This group includes 9 dummy variables for institution rank: [1, 10], [11, 20], [21, 40], [41, 80], [81, 160], [161, 320], [321, 640], [641, 1499] and "no rank". "No rank" contains institutions which could not be recognized by the U.S. News Ranking. Higher rank corresponds to lower prestige. We consider the ranking of the best institution. 10) J_d is the fixed effect of publication venue. The publication venue of a paper is extracted from the journal id in the MAG dataset. 11) Y_d is the fixed effect of publication year. 12) F_d is the fixed effect of academic fields. The academic fields are indicated in level-1 fields from MAG dataset. For all regression analysis in this paper, the standard errors are clustered at individual journal level.

3. Results

3.1. Citation dynamics of interdisciplinary research

To study the association between paper interdisciplinarity and citation dynamics, we begin by categorizing all papers into three equal-sized subsets according to their interdisciplinary levels, i.e., high, medium, and low interdisciplinary research. After that, we calculate for each group the average yearly citations within 10 years after publication, finding that low interdisciplinary research systematically shows lower yearly citations compared to its counterparts, consistent with earlier studies (Zhang et al., 2021). Surprisingly, high interdisciplinary research tends to reach its citation peak substantially later than low interdisciplinary research, suggesting a delayed citation accumulation pattern (Fig. 1(b)). The results are robust with respect to different scientific fields and citation impact (Fig. S7). We find that the time to reach the citation peak calculated from average yearly citation curves is, on average, 7 years for high interdisciplinary research compared to 5 years for medium interdisciplinary and 3 years for low interdisciplinary research (Fig. 1(c)). To further support the significance of this difference, we employ a bootstrapping method. Specifically, for each specific interdisciplinary level, we randomly sample papers with replacement, and calculate the bootstrap peak time by assessing the average yearly citations after publication for these papers. We perform 100 realizations to obtain the distributions of bootstrap peak time. Finally, we find that the bootstrap peak times of papers in the bottom 25 % interdisciplinary level, 26–50 % interdisciplinary level, 51–75 % interdisciplinary level, and the top 25 % interdisciplinary level center around 3, 4, 5, and 7 years, respectively. We find that the difference is statistically significant (p-value <0.001). Thus, these results suggest that collectively, high interdisciplinary research tends to exhibit substantial delayed citation accumulation patterns, which prompts us to ask a further question: Can we observe similar phenomena when considering microscopically (i.e., the citation peak for individual papers)?

3.2. *When is the citation peak of individual papers?*

To address this question, we systematically investigate the citation dynamics for individual papers. We define the peak time of a paper as the time it takes to reach its citation peak after publication, denoted as T_m. To ensure that the peak is sufficiently high compared to the background, the citations at the peak must exceed a threshold (we consider the threshold as the average citations plus two standard deviations for all yearly citations of the paper, as shown by the horizontal dashed line in Fig. 2(a)). Here, we ignore papers without citations or T_m, accounting for 30 % of the sample. Fig. 2(a) and (b) provide illustrations of yearly citations for papers. Specifically, Fig. 2(a) shows a paper that exceeds its threshold with 11 citations at $T_m = 2$, whereas the paper in Fig. 2(b) is above a threshold of 133 citations at $T_m = 45$. Note that the one with larger T_m shows substantially higher interdisciplinarity. Note that the random fluctuation at year 23 in Fig. 2(b) does not affect the overall results.

We find that papers with higher levels of interdisciplinarity exhibit significantly longer average T_m compared to papers with lower interdisciplinary level, as T_m increases monotonically with paper interdisciplinarity (Fig. 2(c)). Specifically, as paper interdisciplinary level increases from the bottom 5 % to the top 5 %, their average T_m increases from 7.1 years to 8.6 years, by a factor of 20 % (t-test p-value <0.001). We repeat our analysis in several directions to further support our observations. When we calculate T_m without applying any citation threshold, the outcomes remained consistent with our main findings (Fig. 2(d)). We also repeat all analyses using only 10-year or 20-year citation windows and find that the window size does not influence the main results (Fig. 2(e), (f)). We define T_m using a 3-year-moving average of individual paper yearly citations, and find similar results (Supplementary Material S4.3 and Fig. S8). We further group papers according to their scientific disciplines, finding similar results (Fig. 2(g)). Specifically, high interdisciplinary research in medicine, chemistry, biology and physics (which collectively constitute nearly 70 % of all papers) waits for 2.7 %, 7.2 %, 29.2 %, 21.6 % more time to reach its citation peak compared to low interdisciplinary research, respectively (p-values for all cases are smaller than 0.001). These results support and quantify the hypothesis that high interdisciplinary research, on average, experiences delayed citation impact, whereas low interdisciplinary research tends to garner attention more quickly.

This pattern is amplified when we focus on papers with the most delayed citation peak (i.e., in the top 5 % T_m among papers

Table 1
Relationship between paper interdisciplinarity and T_m. Standard errors are shown in parentheses, and are clustered at individual journal levels.

	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8
Rao-Stirling Diversity	1.596***	2.060***	1.419***	1.417***	1.378***	0.918***		
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.060)		
True Diversity							0.284***	
							(0.018)	
DIV								63.896***
								(3.238)
Log(#refs)		−0.723***	−0.260***	−0.254***	−0.218***	−0.115***	−0.111***	−0.172***
		(0.002)	(0.003)	(0.003)	(0.003)	(0.010)	(0.010)	(0.011)
Log(Team Size)		−1.114***	−0.238***	−0.235***	−0.241***	−0.121***	−0.120***	−0.121***
		(0.003)	(0.004)	(0.004)	(0.004)	(0.013)	(0.013)	(0.013)
First author academic age				−0.003***	0.001	0.001**	0.001**	0.001**
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Last author academic age				−0.004***	0.001	0.000	0.000	0.000
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average academic age				−0.002**	0.014***	0.007***	0.007***	0.006***
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
First author h-index					−0.014***	−0.013***	−0.013***	−0.013***
					(0.001)	(0.001)	(0.001)	(0.001)
Last author h-index					−0.007***	−0.001**	−0.001*	−0.001*
					(0.001)	(0.001)	(0.001)	(0.001)
Average author h-index					−0.044***	−0.014***	−0.014***	−0.014***
					(0.001)	(0.001)	(0.001)	(0.001)
Constant	7.201***	10.014***	8.180***	8.226***	8.214***	7.926***	7.777***	8.126***
	(0.006)	(0.008)	(0.009)	(0.009)	(0.009)	(0.034)	(0.037)	(0.031)
Institutional rank FE						YES	YES	YES
Publication venue FE						YES	YES	YES
Academic field FE			YES	YES	YES	YES	YES	YES
Publication year FE			YES	YES	YES	YES	YES	YES
Sample Size	11,049,705	11,049,705	11,049,705	11,049,705	11,049,705	11,049,705	11,049,705	11,049,705
Adj R-squared	0.001	0.023	0.086	0.086	0.087	0.126	0.126	0.126

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.001$.

published in the same year). Papers with the top 5 % interdisciplinary level are almost 44 % more likely to exhibit high T_m, i.e., being in the top 5 % of T_m values. By contrast, low interdisciplinary research is less represented among papers with high T_m values (Fig. 2(h)). Interdisciplinary research also shows higher maximal impact (denoted by C_m). We plot the average C_m as a function of paper interdisciplinarity for papers within the top 5 % T_m, finding significant positive association (Fig. 2(i)). Specifically, among all papers in the top 5 % T_m values, high interdisciplinary research, in the top 5 % of interdisciplinary levels, on average, attracts 54.1 % more citations at year T_m, compared to low interdisciplinary papers in the bottom 5 % (t-test p-value <0.001). Finally, we also focus on 10-year and 20-year citation window and calculate the time to reach the half citation for individual papers published each year (i.e., impact time Wang et al., 2013), finding that high interdisciplinary research consistently show longer impact time than low interdisciplinary research (Fig. 2(j), (k)). These results indicate that interdisciplinary research not only shows delayed citation impact, but also has significantly higher maximal citation impact.

We also directly compare the distribution of T_m for low, medium, and high interdisciplinary papers, finding that these distributions show significant differences (Supplementary Material S4.4 and Fig. S9). Considering that high interdisciplinary papers tend to attract more citations, and accumulating citations takes time, we repeat the analysis for papers with a similar number of citations received within 10 years after publication (i.e., C_{10}) across different time periods. We consistently find that the average T_m of high interdisciplinary papers is higher (Supplementary Material S4.4 and Fig. S10). Finally, we utilize the beauty index (Ke et al., 2015) and impact time using all-year citation windows to quantify citation dynamics, and the alternative methods yielded similar results (Figs. S11 and S12). Finally, we repeat the main results using the Dimensions data, finding consistent results (Fig. S15). In summary, we use large-scale scholarly datasets to demonstrate the consistent positive relationship between paper interdisciplinarity and the time to reach its citation peak, both macroscopically and microscopically.

Can the positive association between paper interdisciplinarity level and *Tm* be attributed to other factors? To investigate this, we employ the fixed effect regression method (The correlation matrix among independent variables is shown in Table S1). Correlation

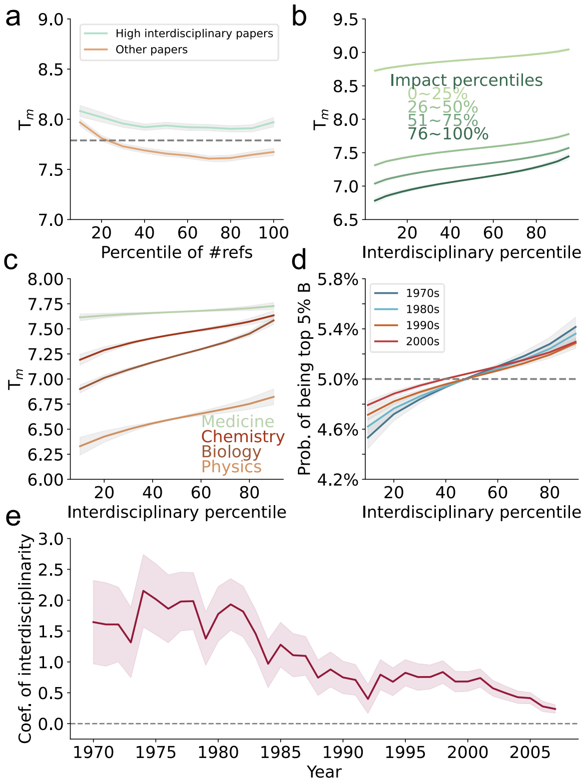

Fig. 3. Delayed citation impact of interdisciplinary research across impact levels, different scientific fields and time periods. (a) T_m for interdisciplinary research is higher than regular papers for different number of references, while we adjust for possible confounding factors in the regression analysis. We consider papers with the top 30 % interdisciplinary nature as high interdisciplinary research, whereas the remaining papers are categorized regular research. The graph shows that high interdisciplinary research has larger and stable T_m above the base line (dashed line) across different number of references, and likewise, compared to regular research. (b) T_m as a function of interdisciplinary percentile across various citation levels. Curves are colored by different impact percentiles (i.e., the number of citations captured within 10 years after publication). T_m increases faster for papers of higher impact percentiles. (c) T_m as a function of interdisciplinary percentile for medicine, chemistry, biology and physics. (d) The probability of being sleeping beauties (i.e., the probability of being the top 5 % B index in the same year) as a function of interdisciplinary level across time periods, showing significant increasing trends with respect to interdisciplinarity. Shaded areas represent 95 % confidence intervals. (e) The regression coefficients of interdisciplinarity on T_m as a function of time. The shaded area represents the 95 % confidence interval. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

matrix indicates no strong collinearity in the regression. First, our findings reveal that the positive effect of paper interdisciplinarity on *Tm* is statistically significant without any controlling variable (Table 1, Column 1, p-value <0.001). Recognizing that variables such as the number of references and team size can be associated with both citation patterns and interdisciplinarity (Wang et al., 2015), we introduce controls for these factors, which yield significant positive results (Table 1, Column 2, p-value <0.001). Furthermore, considering that time and scientific discipline may influence T_m, we use time and scientific field fixed effects to account for these potential effects, obtaining consistent results (Table 1, Column 3, p-value <0.001). To address the impact of academic age, we include controls for the age of the first author, the last author, as well as the average age of the team, confirming further the robustness of our findings (Table 1, Column 4, p-value <0.001). In addition, we incorporate controls for author citation impact by including the h-index of the first author, the last author, and the average h-index of the research team (Table 1, Column 5, p-value <0.001). Finally, we introduce institution and journal fixed effects (Table 1, Column 6, p-value <0.001). Our results consistently demonstrate the positive impact of paper interdisciplinarity on T_m, underscoring the robustness and strength of our findings. It is important to note that we also confirm the relationship using alternative interdisciplinary indicators (Table 1, Column 7 and Column 8, p-value <0.001).

To further strengthen our results, Fig. 3(a) shows the average T_m as a function of the number of references for high interdisciplinary papers (top 30 % high interdisciplinary level) and other papers, while controlling for team size, author academic impact, author academic age, institution rank, scientific field, publication time, and publication venue (detailed information regarding the regression settings can be found in the Methods). We find an intriguing pattern that high interdisciplinary papers are characterized by larger T_m compared to others regardless of their number of references. Specifically, high interdisciplinary papers take, on average, 8.6 % longer time to reach their citation peak while adjusting for possible factors (see Table 1, and Table S2 for the full regression table). High interdisciplinary research takes longer time to reach the citation peak regardless of its ultimate academic impact (Fig. 3(b)). Specifically, high impact papers in the top 5 % interdisciplinary nature need to wait 9.8 % more time compared to those in the bottom 5 % interdisciplinarity with similar citations, whereas for low impact papers the slope flattens (Fig. 3(b)). We further assess T_m separately for the fields of medicine, chemistry, biology and physics, finding that these patterns persist across these four major scientific fields (Fig. 3(c)). Among these four fields, we find that the delayed citation impact of interdisciplinary research is more prominent in biology and physics.

We further support our findings by considering sleeping beauties in science (Ke et al., 2015). Specifically, we compute directly the beauty index (i.e., B index) for papers with different interdisciplinary levels (see details in the Methods and Supplementary Material S3.2) (Ke et al., 2015). A high B index indicates a longer period of “sleeping” before experiencing a surge in citations. Fig. 3(d) shows the probability of being classified as sleeping beauties (i.e., belonging to the top 5 % in terms of B index for the same publication year) across different interdisciplinary levels, while we adjust for other factors using regression analysis (Table S2). We find that high interdisciplinary papers tend to have higher probability to become sleeping beauties across various time periods. Specifically, in 1970s, papers in the top 10 % in terms of interdisciplinarity have a 25 % higher likelihood of becoming sleeping beauties compared to their counterparts in the bottom 10 % in terms of interdisciplinarity. The slope decreases in recent years, as the B index tends to be smaller due to shorter citation windows. This observation is in line with the fact that papers with high B index are more likely to attract citations from different disciplines (Ke et al., 2015). Finally, to account for potential temporal effects, we examine the relationship between paper interdisciplinarity and T_m through separate regressions each year (Fig. 3(e)). Remarkably, we consistently observe the same results across different years, reinforcing the robustness of our findings.

We perform additional regression analyses to support our findings. To further study the dynamical patterns underlying individual paper citation dynamics, we fit each paper’s citation dynamics to the WSB model (Wang et al., 2013) (detailed model descriptions are shown in Methods and Supplementary Material S3.1). We then replace T_m with relevant parameters in the model, and conduct the regression analysis, finding similar results (Fig. S13(b)). We also directly calculate the individual paper’s impact time measured as the time to arrive a paper’s half citations (Supplementary Material S5.1 and TableS2). To eliminate the effect of unobservable features of individual scientists, we control for individual characters by adding individual fixed effect in the regression analyses (Yang, Tian, Woodruff, Jones, & Uzzi, 2022), and we again find robust results (Table S3). We also find that Poisson regressions yield similar results (Table S4). To further eliminate possible temporal bias, we conduct regressions separately for each year, but only focus on 10 % highly cited papers. We find that the positive association remains stable (Fig. S16). Finally, we repeat the regression analysis using the Dimensions data, while controlling for the number of references, team size, publication year, scientific fields, as well as publication venue. We find robust associations (Table S5).

3.3. Can the Matthew effect affect the delayed citation impact?

To understand the potential factors contributing to our findings, we theorize such delay in relevant factors. Inspired by the literature on the sociology of science, we first investigate whether such delayed citation impact would be affected by the Matthew effect, which suggests the rich-get-richer effect in science (Merton, 1968). Several caveats we observed are intriguing. First, we find that T_m decreases significantly from 9 years to less than 7 years as a function of the journal impact factor, suggesting that papers published in high impact journals attract academic attention considerably faster than their counterparts in less prestigious journals (Fig. 4(a)). Also, Fig. 4(b) shows that papers written by prominent scientists attracts approximately 4.8 % faster citation impact than research written by less well-known researchers, consistent with the fact that early citation premium probably rooted in the reputation or status of authors (Petersen et al., 2014). However, we find that the positive gap of T_m between high and low interdisciplinary papers written by scientists or institutions with similar reputations, and published in journals with similar rankings is significant, suggesting the delayed citation impact goes beyond the Matthew effect (Fig. 4(a) and (b)). More precisely, high interdisciplinary papers published by prestige journals and written by prominent scientists, on average, wait for roughly 3 % longer time to arrive to the citation peak,

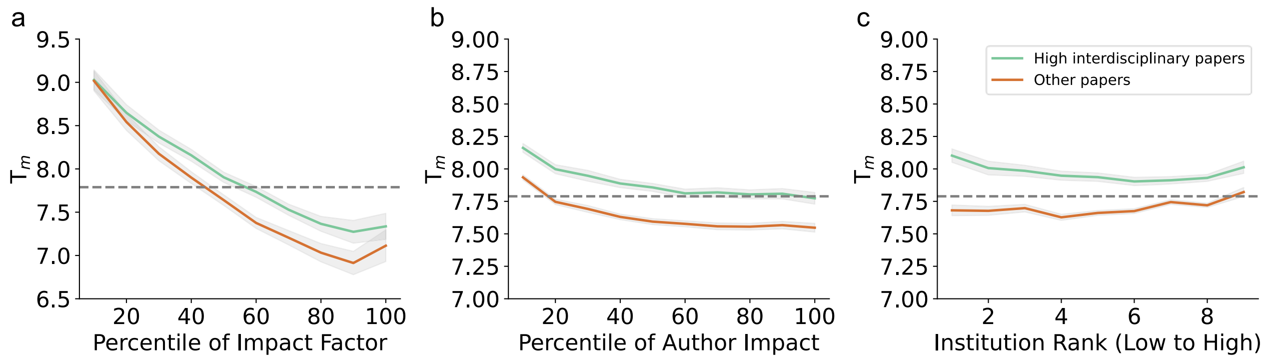

Fig. 4. The effect of the Matthew effect on the citation delay. Papers with high interdisciplinarity (green curve) show higher T_m compared to regular papers (red curve) for (a) different journal impact, (b) different author impact, and (c) different institution rank. Shaded areas represent 95 % confidence intervals. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

compared to regular papers with similar characteristics. We also use institutional rank as another proxy for reputation. We find that the difference of T_m between high interdisciplinary research and its counterparts is stable, i.e., high interdisciplinary research affiliated by prestigious institutions takes 5.5 % longer time to reach the citation peak compared to regular research by institutions with similar reputation (Fig. 4(c)). Together, these results imply that high interdisciplinary research from high status journals/researchers/institutions also exhibits delayed citation impact compared to regular research of similar features.

3.4. What factors attribute to the delayed citation impact?

Motivated by team science literatures, we here study the organizational features of each paper (i.e., team size). To this end, we look into the question whether the T_m gap between high and low interdisciplinary research varies across different team sizes. For papers with less than 7 authors, high interdisciplinary research still shows delayed citation impact compared to regular research, by 2.9 % (Fig. 5(a)). Interestingly, we do find indications that the difference of T_m between high and low interdisciplinary research diminishes for large teams, which is consistent with the fact that large teams often publish articles through incorporating novel ideas while not abandoning conventionality (Uzzi et al., 2013). In light of this finding, we therefore estimate the content conventionality of each paper using journal pairs within the reference list (Uzzi et al., 2013), finding that combining high conventional wisdom shrinks the gap of T_m between high and low interdisciplinary research (Fig. 5(b), see also Supplementary Material S6.3). We further test whether content feature acts as a possible mechanism. We find that interdisciplinary science tends to be unconventional, and the partial correlation between interdisciplinarity and T_m becomes smaller when we control for paper conventionality (Supplementary Material S6.3, Table S10). Together, these findings are consistent with what Cole has previously written (Cole, 1970), "*... the delayed recognition was primarily the result of content rather than the author's prestige*".

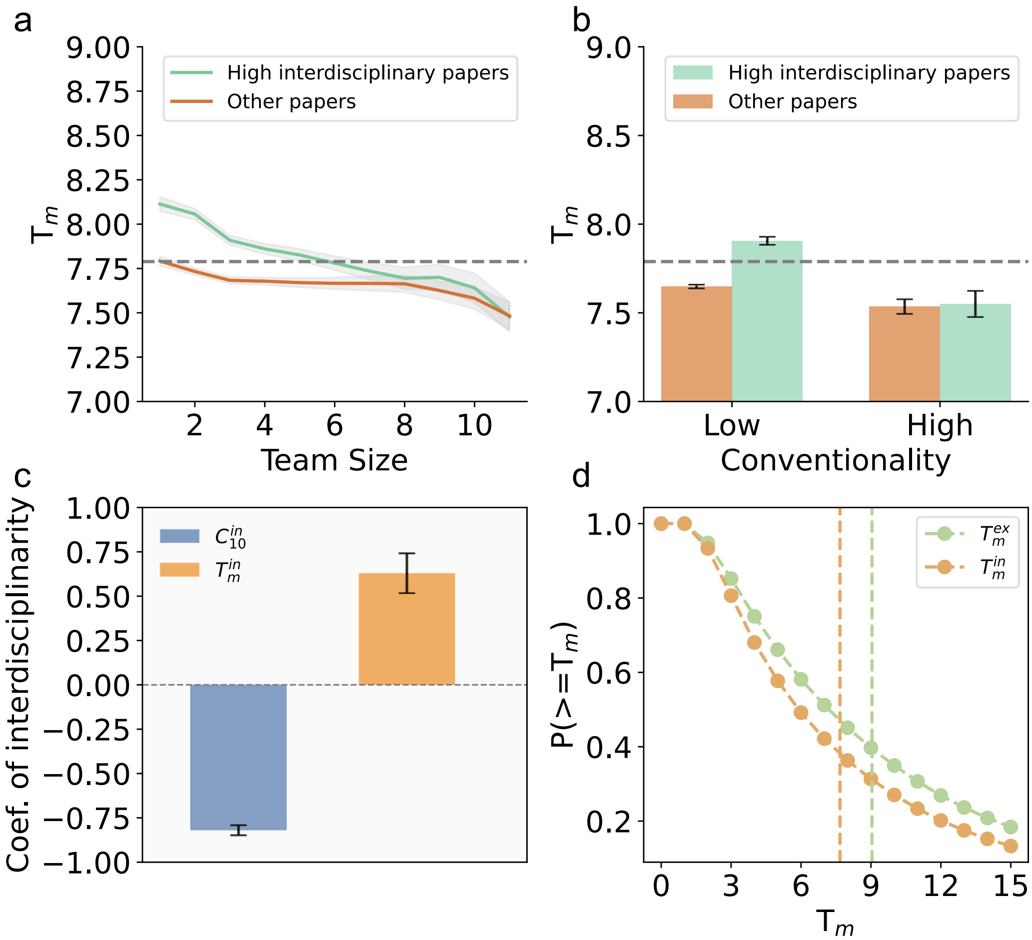

Fig. 5. Teams, content features and knowledge diffusion. (a) The difference of T_m between papers with high interdisciplinarity (green curve) and regular papers (red curve) shrinks as team size increasing. (b) The difference of T_m between high interdisciplinary papers and regular papers dwindles while adding high conventionality (the top 10 % conventionality) term. (c) Interdisciplinary research shows longer time to reach scientific impact and less citations from internal fields. Shaded areas and error bars represent 95 % confidence intervals. (d) The complementary cumulative distribution of T_m for internal and external citations. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Given that interdisciplinary research often has broad citation impact (Gates, Ke, Varol, & Barabási, 2019), we investigate the extent to which knowledge diffusion between different fields (external) and within fields (internal) contributes to the delayed citation impact of interdisciplinary research. We classify citations for each paper into two categories, i.e., external citations originating from other scientific fields and internal citations coming from the same field. We conduct regression analysis with the number of internal citations, or the time to reach the internal citation peak as dependent variable. As shown in Fig. 5(c), we find that the association between paper interdisciplinarity and internal long-term impact is significantly negative, whereas the association between interdisciplinarity and internal *Tm* is significantly positive, while adjusting for all other covariates. This result indicates that interdisciplinary research gains less internal citations and experiences delayed recognition within the internal community, which may suggest that there exists a bias against interdisciplinary research within scientific domains. Furthermore, knowledge diffusion to external fields requires longer time compared to internal fields (Fig. 5(d)). This observation suggests that interdisciplinary research, which affect external fields, exhibits a slower rate of knowledge dissemination, thereby contributing to its delayed citation impact.

4. Conclusions

Despite intensive efforts to understand the features of interdisciplinary science and citation impact, there is lack of empirical evidence regarding the epistemic barriers faced by interdisciplinary research using large-scale datasets from various scientific disciplines. In this paper, we focus on the time to reach the citation peak for individual papers. Instead of examining static citations for various citation windows or papers from selected years (Chen et al., 2022; Wang et al., 2015), we quantify, both microscopically and macroscopically, how the time to reach the citation peak is affected by paper interdisciplinary levels, using a large-scale scholarly dataset. We find that highly interdisciplinary research exhibits delayed citation impact, as it takes longer time to reach its citation peak.

Our finding of delayed citation impact in interdisciplinary research may have multiple reasons. The difference of the time to reach citation peak between highly interdisciplinary and regular research in prestigious venues, or by prominent authors and famous institutions remains stable, suggesting that the delayed citation impact is independent of the Matthew effect. Additionally, we find that the difference becomes much smaller for papers written by large teams or through combining high conventional wisdom, which is consistent with the claim about innovative strategies of large teams (Uzzi et al., 2013). Along this line, we find indications that combining conventional wisdom partly explains the effect, as the association between paper interdisciplinary levels and the T_m becomes smaller. This suggests that highly interdisciplinary research that absorbs wisdom spanning diverse disciplines may be far away from the classical community. Finally, we hypothesize that knowledge diffusion may also contribute to such delay, as paper interdisciplinarity shows consistent negative correlations with citations within internal scientific domains, and knowledge diffusion to foreign disciplines requires substantially longer time.

Our work differs significantly from prior studies in the following three aspects. First, we develop a simple measure T_m to depict the time to reach the major citation impact for individual papers. Second, instead of distinguishing the effects of different aspects of interdisciplinarity on citations (Wang et al., 2015), we use integrated interdisciplinary measures to study the associations between interdisciplinarity and T_m, and validate our results using several interdisciplinary metrics. Third, we quantify the relationship between the level of interdisciplinarity and T_m using large scholarly data across multiple years and multiple scientific domains. Although we observe general delayed citation impact patterns across almost all scientific domains, such relationship is more pronounced in biology and physics than that in medicine. Finally, comparing to earlier research, we untangle underlying forces behind the delayed citation impact of highly interdisciplinary research and relate this to various factors, such as convent conventionality and knowledge diffusion.

Taken together, given the fact that interdisciplinary research is often considered as the space for innovative research that is the key to future economic growth, policy makers who wish to promote interdisciplinary research should notice such delayed citation impact. Specifically, highly interdisciplinary research may show substantial disadvantages using bibliometric indicators such as the journal impact factor that explicitly use very short citation windows. Funding agencies that extensively use bibliometric indicators need to develop or refine current evaluating system to foster interdisciplinary research. Moreover, our results also provide insight for institutions that hire or nurture junior scientists engaging in interdisciplinary research. Namely, too much focus on short-term citations may disincentive interdisciplinary research. Simultaneously, researchers engaging in highly interdisciplinary research often attain better funding performance in the long run (Sun, Livan, Ma, & Latora, 2021), which depicts long-term advantage propensity of conducting highly interdisciplinary research. We advocate the awareness of such bias, especially for research administrators (Wang, Veugelers, & Stephan, 2017). Finally, our analysis indicates that such delayed citation impact is an inherent nature of knowledge production process such as scientific paradigms (Kuhn, 1962) or knowledge diffusion across scientific domains (ED Rinia et al., 2001), which may have long lasting effects on individual scientists, funding allocations (Bromham et al., 2016), and prize agencies (Szell et al., 2018).

Our work has limitations. First, we calculate the interdisciplinarity of individual papers based on their reference lists. There are alternative diversities, such as discipline diversity, ethnic diversity, and collaboration diversity (Adams, 2013; AlShebli, Rahwan, & Woon, 2018; Zeng, Fan, Di, Wang, & Havlin, 2021; Zheng, Li, & Wang, 2022). Additionally, our research is of a correlational nature. It is also important to note that the impact of scientific research extends beyond just citations. Many other aspects of impact, such as societal and economic impact, related to interdisciplinary research remain to be explored. Using citations as the sole measure of impact can also raise some concerns (Aksnes, Langfeldt, & Wouters, 2019; Catalini, Lacetera, & Oettl, 2015). Nevertheless, we find strong positive relationships between paper interdisciplinarity and time to reach the citation peak, and such association goes beyond the Matthew effect and may be influenced by factors such as content conventionality and knowledge diffusion among scientific disciplines. Based on these conclusions of our research, and motivated by examples about hurdles of interdisciplinary research (Leahey, Beckman, & Stanko, 2017), it is interesting to see whether interdisciplinary education background has similar effects on individual scientists.

Data and materials availability

All data are available in the main text or the supplementary materials. Those who are interested in raw data of Dimensions should contact Digital Science.

CRediT authorship contribution statement

Yang Zhang: Data curation, Formal analysis, Visualization, Writing – original draft. **Yang Wang:** Conceptualization, Funding acquisition, Supervision, Writing – review & editing. **Haifeng Du:** Investigation, Conceptualization. **Shlomo Havlin:** Conceptualization, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no conflict of interest.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.joi.2023.101468.

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