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Interdisciplinarity, Temporal Diversity, and Scientific Impact: Perspective on References

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Abstract: Building on the concept of interdisciplinarity, this paper proposes a measurement framework for temporal diversity, quantifying it into four dimensions: temporal richness, temporal imbalance, temporal disparity, and temporal depth. This study meticulously analyzes the temporal trends and distribution characteristics of interdisciplinarity and temporal diversity, as well as the career evolution patterns of high-level scientists, using 38,879,575 scientific papers from the Microsoft Academic Graph database spanning from 1950 to 2020. Furthermore, it explores the relationship between interdisciplinarity, temporal diversity, and scientific impact. The findings reveal that: (1) Interdisciplinarity and temporal diversity of papers exhibit a consistent growth trend but differ in their field distribution. (2) Both interdisciplinarity and temporal diversity indicators show heterogeneous distribution characteristics, such as scale-free distribution, and there is a weak correlation between them. (3) During the careers of high-level scientists, both interdisciplinarity and temporal diversity show significant growth trends, largely attributable to the increase in the number of references in their papers. (4) Interdisciplinarity and temporal diversity have opposite effects on scientific impact: interdisciplinarity significantly promotes scientific impact, while temporal diversity significantly inhibits it; a combination of strong interdisciplinarity and weak temporal diversity has the highest

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probability of becoming a disruptive hotspot paper. The temporal diversity measurement framework proposed in this paper enriches the theories of knowledge integration and interdisciplinarity, providing insights for science and technology policy and academic evaluation.

Key Words: Interdisciplinarity; Temporal Diversity; Citation Network; Scientific Career.

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1. Introduction

Research models characterized by interdisciplinarity are believed to foster the emergence of new discoveries, insights, concepts, and technologies (Gates et al., 2019). Interdisciplinarity reflects the complexity and richness of the distribution of scientific knowledge across domains (Stirling, 2007) and represents the horizontal dimension of scientific knowledge (Zhang et al., 2024, 101468). Corresponding to this is the vertical dimension of the knowledge base, which captures the process through which existing research traces its origins within a broad and diverse network of knowledge (Sheng et al., 2023). A comprehensive understanding of the intrinsic mechanisms linking the knowledge base to scientific impact, from both horizontal and vertical perspectives, is crucial for elucidating the underlying dynamics of knowledge flow. It also holds significant reference value for guiding academic evaluation and informing science and technology policy.

In scientific citation networks, forward and backward citations can reveal the flow and inheritance of scientific knowledge. When the research subject changes, the meaning of citation relationships may also shift; for example, a forward citation link of one paper can also be viewed as a forward citation link of another paper (Zeng et al., 2017, p1) . Citation-related analyses often focus on a paper's future citations, such as dynamic citation prediction(Wang et al., 2013), citation diffusion, scientific "sleeping beauties"(Alex J Yang et al., 2024), literature obsolescence, and scientist impact (Liu et al., 2018). These models or methods reflect the future diffusion or impact of scientific knowledge. In contrast, the inheritance of scientific knowledge can be examined based on a paper’s references. A typical analytical framework in this context is the measurement of interdisciplinarity(Gates et al., 2019; Liu & Sun, 2023; Stirling, 2007), which fully considers the distribution of references across different scientific fields, thereby highlighting the interdisciplinary nature of scientific knowledge. This paper regards *interdisciplinarity as a horizontal analytical perspective, while the vertical analytical perspective corresponds to the temporal distribution of references.*

The current academic community has developed a relatively deep understanding of the horizontal dimension—interdisciplinarity—of scientific knowledge (Gates et al., 2019; Liu & Sun, 2023; Stirling, 2007), but a systematic comprehension of its vertical dimension remains lacking. On one hand, references are historical and static, possessing little predictive value, which often leads to an underestimation of their analytical potential. On the other hand, existing studies typically focus only on the disciplinary or topical information contained within references. Beyond interdisciplinary measurement, theories of innovative recombination in the science of science often consider only the combination of different knowledge topics (Uzzi et al., 2013) , frequently overlooking the temporal combination of references. In reality, scientific fields place strong emphasis on continuity and historical inheritance (Bloom et al., 2020), and the vertical dimension of scientific knowledge is extensive. With the development and application of large-scale literature databases, scientists must consider not only how to sample and combine knowledge from different fields but also how to sample and combine knowledge from different years (Evans, 2008). Both the horizontal and temporal distribution of knowledge are crucial to the quality and future impact of a paper. However, systematic research specifically addressing the temporal combination of scientific knowledge is still absent, partly due to the lack of a robust analytical framework for quantifying the temporal distribution characteristics of a paper's references.

To address this gap, building on the concept of interdisciplinarity, this paper innovatively proposes a measurement framework for temporal diversity, comprising four key dimensions: *temporal variety, temporal imbalance, temporal disparity, and temporal depth.* This framework for temporal diversity is designed to comprehensively characterize the vertical distribution of scientific knowledge. It corresponds to, complements, and integrates organically with the framework for interdisciplinarity. Based on this dual perspective of the horizontal and vertical distribution of the scientific knowledge base, this study conducts a large-scale empirical analysis of 38,879,575 papers across 19 fields from the Microsoft Academic Graph database, covering the period from 1950 to 2020. The analysis reveals the temporal trends, disciplinary variations, distribution characteristics, interrelationships, and career evolution patterns concerning scientific interdisciplinarity and temporal diversity. Furthermore, it delves deeper into the complex relationship between *interdisciplinarity, temporal diversity,* and *scientific impact.* The aim is to theoretically enrich the understanding of knowledge integration and innovation, while also providing insights for science and technology policy and academic evaluation in practice.

2 Literature Review and Data

2.1 Literature Review

In formal academic exchanges, scholars typically cite existing research to establish the theoretical or methodological foundation of their own work. The references they choose reflect the scientific knowledge base underpinning their studies (Fortunato et al., 2018, 6379). From the perspective of references, the scientific knowledge base can be examined along two dimensions: the *disciplinary/content* dimension and the *temporal* dimension. These correspond respectively to the horizontal diffusion of knowledge across fields and the vertical evolution of knowledge over time. The former has formed the basis for research on the prominent theme of interdisciplinarity(Gates et al., 2019; Liu & Sun, 2023; Stirling, 2007), while the latter can be defined as the *temporal diversity* of a publication.

The *interdisciplinarity* of a paper primarily manifests as the complexity of the disciplinary distribution within its knowledge base(Zhang & Wu, 2017). The concept of interdisciplinarity is often traced to the notion of diversity in biology. Viewing knowledge integration through the lens of references allows frameworks originally designed to measure biological diversity to be applied to the context of the science of science (Gates et al., 2019). Stirling proposed a theoretical framework and indicators for interdisciplinary research, arguing that interdisciplinarity should encompass at least the dimensions of diversity, balance, and disparity (Stirling, 2007). Leydesdorff and Rafols employed Shannon entropy, betweenness centrality, and distance matrices to assess the interdisciplinarity of publications, concluding that a single indicator might be insufficient for identifying interdisciplinary literature(Leydesdorff & Rafols, 2011). Rafols and Meyer (Rafols & Meyer, 2010) refined the analytical granularity by incorporating the dimension of coherence alongside variety, advancing comparative studies of emerging scientific and technological fields(Ding et al., 2014). Other scholars have focused on the impact or application of the disciplinary dimension of references. For instance, Ren et al. analyzed the disciplinary distribution of prize-winning research and its cited publications in natural sciences to explore the significant influence of interdisciplinary knowledge integration(Ren et al., 2023). Ke measured the disciplinary distribution of references by statistically analyzing their diversity, disparity, and balance, and further examined the social impact of interdisciplinary research based on this analysis(Ke, 2023).

This paper posits that the *temporal diversity* of a publication is reflected in its incorporation of knowledge from multiple temporal nodes. Current scholarly discussions on the temporal diversity of publications remain relatively limited. Existing research primarily focuses on the age of references (Pan et al., 2018) as the object of analysis. This involves modeling patterns in the age distribution of references or describing its statistical characteristics (Ghaffari & Wilson, 2023), often while examining the relationship between these distributional features and scientific impact, with the aim of predicting forward-looking research. For instance, Gupta conducted a statistical analysis of the age of references cited in seminal literature across different developmental stages within the field of genetics, exploring the applicability of various theoretical probability functions to the age density of cited references(Gupta, 1997). Jaric et al. assessed the relationship between the age of references and changes in publication rates within research fields, proposing two indicators—relative reference age and the proportion of references published in the preceding two years—to mitigate errors arising from publication lag(Jaric et al., 2014). Stacey fitted gamma distributions to the age distributions of references across multiple fields, confirming the stability of the gamma distribution model for such data and proposing derived indicators as important references for predicting knowledge growth(Stacey, 2021). Additionally, Reisz et al. also conducted statistical analyses on the relationship between the characteristics of reference age distribution and citation performance(Reisz et al., 2022).Thus, it is evident that current research on the characteristic elements of the vertical dimension of the knowledge base remains relatively narrow and fragmented. A systematic framework for measuring the transtemporality of scientific knowledge is notably lacking.

Research on the horizontal dimension of the knowledge base has already developed systematic analytical frameworks for interdisciplinarity along with a rich array of measurement indicators. In comparison, studies addressing the vertical dimension of the knowledge base remain at a preliminary stage, largely confined to surface-level analyses such as descriptive statistics concerning the age of references. Consequently, this paper will draw upon interdisciplinary theories and methodologies to innovatively propose a measurement framework for the temporal diversity of academic publications. Furthermore, by simultaneously considering both the interdisciplinary and temporal diversity characteristics of publications, we will conduct a systematic empirical analysis centered on the relationship between knowledge integration and scientific impact. This aims to elucidate the underlying mechanisms and pathways through which these factors interact, thereby providing a scientific foundation for research management and policy formulation.

2.2 Data Sources and Processing

This study employs the Microsoft Academic Graph (MAG) as the source for publication and citation data(Wang et al., 2020). The MAG encompasses over 200 million publications from 1800 to 2021 and more than 15 billion citation links, covering various document types including journal articles, conference papers, preprints, books, and other forms of scientific literature. To ensure data quality, journal articles published between 1950 and 2020 were selected for analysis. Non-journal publication types were excluded due to potentially inconsistent citation patterns across document categories. Furthermore, the journal labels provided by MAG help to control, to some extent, for heterogeneity in paper quality and type. Additionally, only research papers containing at least five references were retained to filter out non-research academic records such as errata, editorials, and letters. Based on the above filtering criteria, the final dataset comprises 38,879,575 papers and 909,136,957 citation links.

The MAG addresses author name disambiguation through a hybrid approach combining machine learning, crowdsourcing, and web data, achieving a high degree of reliability (Wang et al., 2020). A recent study involving manual matching reported a precision of 100% and a recall of 84% within a tested sample (Lin et al., 2023). However, challenges persist in the disambiguation of names, particularly for Asian authors with exceptionally high publication volumes. In analyses at the scientist career level, publication count thresholds were applied to mitigate the potential impact of disambiguation issues.

The MAG provides a structured hierarchical field classification system based on deep learning. This study utilizes two levels of this hierarchy: the first level comprises 19 broad research fields (e.g., Medicine, Physics, Computer Science), and the second level further divides these into 292 subfields. For each paper, the MAG's machine learning model assigns one or more field labels with associated probability scores indicating prediction confidence. In this study's analytical framework, the primary subfield label (level 2) with the highest confidence score was assigned to each paper. The calculation of interdisciplinary indicators and the inclusion of field fixed effects in subsequent analyses are based on these 292 MAG subfields.

3. Measurement Framework, Distribution Characteristics, and Career Evolution

3.1 Measurement Framework for Interdisciplinarity and Temporal Diversity

Building upon the framework proposed by Stirling (Stirling, 2007), this paper decomposes the interdisciplinarity of a publication into several dimensions: *disciplinary variety, disciplinary imbalance,* and *disciplinary disparity*, employing the *Rao-Stirling* index as the overarching measure of overall interdisciplinarity.

For a given paper i, its set of references $R_i = \{r1, r2, \dots\}$ is mapped to a disciplinary distribution vector $F_i = \{field_{r1}, field_{r2}, \dots, field_{rk}, \dots\}$, where $field_{rk}$ denotes the disciplinary field of reference r_k.

- Disciplinary Variety is defined as the number of distinct fields covered by the references of paper$i$.
- Disciplinary imbalance is measured by the normalized Shannon entropy of the distribution of references across these field categories.
- Disciplinary Disparity is represented by the maximum pairwise distance between any two fields present in the references of paper i, defined as $Max\{d_{mn}|m, n \in F_i\}$. Here, d_{mn} signifies the distance between fields m and n calculated based on the entire corpus of publications and their citation networks within the Microsoft Academic Graph: $d_{mn} = 1 - CosSim(V_m, V_n)$, where V denotes the field vector.

· Overall Interdisciplinarity (Rao-Stirling Index) is calculated as $\sum_{m\neq n} d_{mn}p_m p_n$, where p_m、$p_n$are the proportional representations of fields m and n within the references of paper i, respectively, and d_{mn} is the distance between these fields(Stirling, 2007).

This paper proposes for the first time a theoretical and measurement framework for the temporal diversity of scientific knowledge. Temporal diversity refers to the breadth, depth, imbalance, and disparity in the spatio-temporal distribution of scientific knowledge, which can be specifically measured by the temporal distribution of a paper's references. The temporal diversity of a paper is decomposed into three core dimensions: *temporal variety, temporal imbalance*, and *temporal disparity*. Additionally, this paper considers the average age of references as an indicator of temporal depth.

For a given paper $i$and its full set of references $R_i = \{r1, r2, \ldots\}$,the age of its references is mapped to a temporal distribution vector $A_i = \{age_{r1}, age_{r2}, \ldots, age_{rk}, \ldots\}$, where age_{rk} represents the age of reference r_k.

· Temporal Variety is defined as the number of distinct ages (publication years) covered by the references of paper i.

$$temporalvariety = \sum_{r\in R_i} year_r \tag{1}$$

· Temporal Imbalance is measured by the normalized Shannon entropy of the age distribution of the paper's references.

$$temporalImbalance = Shannonentropy_{age} = -\frac{\sum_{i=1}^{Max(variety)} p_\alpha ln(p_\beta)}{ln(Max(variety))} \tag{2}$$

· Specially, $\alpha \in A_i$ represents a specific age within the set of reference ages for paper i, and p_α denotes the proportion of references at that age. $Max(variety)$ represents the maximum possible value of temporal variety, which in this study is 178.

· Temporal Disparity is represented by the maximum age distance among the references of paper i, defined as

$$temporaldisparity = Max\{|age_{rk} - age_{rl}| \,|\, age_{rk}, age_{rl} \in A_i\} \tag{3}$$

Where $|age_{rk} - age_{rl}|$ denotes the difference between the ages of references r_k and r_l, equivalent to the absolute difference in their publication years.

· Temporal Depth is indicated by the average age of the references in paper i, defined as

$$temporaldepth = Mean\{age_{rk} \,|\, age_{rk} \in A_i\} \tag{4}$$

where age_{rk} is the age of reference rk.

It is noteworthy that this framework employs "imbalance" (and by extension, its inverse interpretation through the entropy measure) rather than "balance" as a component. This choice aligns with the definition of the normalized Shannon entropy and the conceptualization of interdisciplinarity/temporal diversity. When a paper cites literature from only a single field or a single year, its normalized Shannon entropy is 0, reflecting minimal interdisciplinarity or temporal diversity.

Furthermore, subsequent findings in this study confirm the conceptual consistency of this measure with other indicators.

The measurement frameworks for interdisciplinarity and temporal diversity are illustrated in Figure 1. They examine the knowledge base from the perspectives of horizontal (disciplinary) and vertical (temporal) distribution, respectively. Both frameworks characterize the patterns and features of the scientific knowledge base through the shared dimensions of variety, imbalance, and disparity, offering complementary analytical lenses.

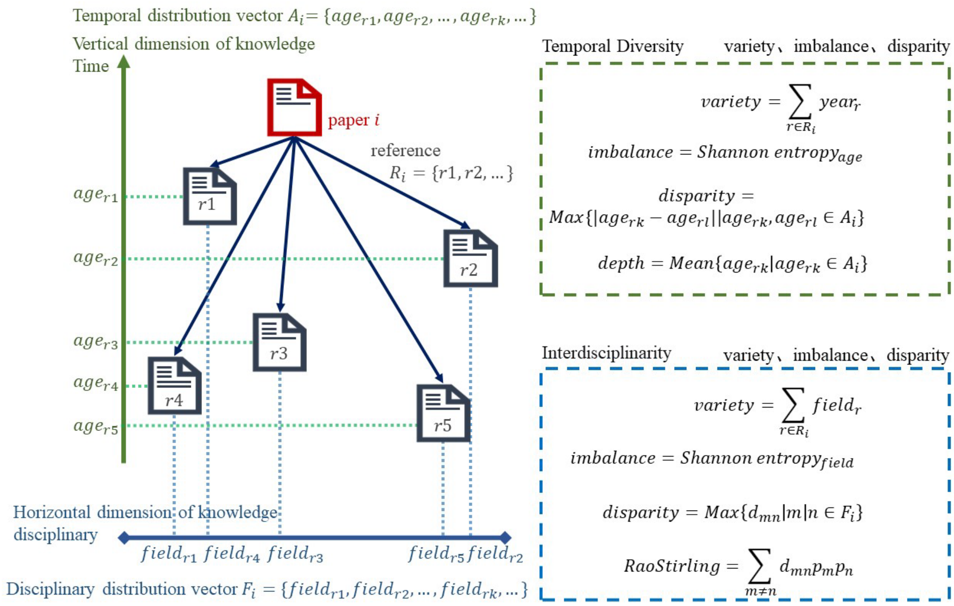

Figure 1. Measurement Framework for the Interdisciplinarity and Temporal Diversity of Scientific Knowledge

3.2 Temporal Trends in Interdisciplinarity and Temporal Diversity

This study analyzes the temporal trends of interdisciplinary and temporal diversity indicators across 38,879,575 papers, with the results presented in Figure 2. *Disciplinary variety, disciplinary imbalance, disciplinary disparity*, and the overall *interdisciplinary measure (Rao-Stirling index)* all exhibit significant upward trends. The increasing trend in disciplinary variety indicates that papers demonstrate progressively stronger knowledge richness and horizontal breadth. The rising trends in disciplinary imbalance and disparity suggest that, despite the increase in disciplinary variety, a small subset of disciplinary knowledge still constitutes a larger proportion, and this heterogeneity is gradually intensifying. The upward trend in overall interdisciplinarity reflects a gradual shift in scientific fields from independent, specialized research models toward more integrated, interdisciplinary approaches.

Temporal diversity shows trends largely consistent with those of interdisciplinarity, namely, significant upward trends in temporal variety, temporal imbalance, temporal disparity, and temporal depth. This indicates that, as scientific knowledge continues to accumulate, papers exhibit increasing vertical depth and span of knowledge. Furthermore, they demonstrate a growing degree of imbalance, meaning that knowledge from a limited number of time periods accounts for a dominant proportion.

Different scientific fields exhibit distinct trends in interdisciplinarity and temporal diversity. The interdisciplinarity indicators in the humanities and arts are significantly lower than those in fields such as science and engineering, biomedicine, and social sciences, with a relatively smaller increase over time. Social sciences show the fastest growth in disciplinary variety and imbalance, while science and engineering demonstrate the most rapid increase in disciplinary disparity and the overall Rao-Stirling interdisciplinarity index. The field of biomedicine also exhibits a strong upward trend in interdisciplinarity.

In terms of temporal diversity, the humanities and arts display notably higher temporal disparity and temporal depth compared to other fields. While their temporal variety and imbalance were relatively high in earlier periods, they have gradually been surpassed by other fields over the past decade. This reflects a tendency in the humanities and arts to emphasize citations of classical literature and traditional theories. In contrast, fields such as biomedicine have consistently maintained lower temporal disparity and temporal depth, indicating rapid knowledge turnover and the continuous emergence of new research findings. These patterns suggest that the paradigmatic characteristics of different disciplines shape their preferences for knowledge integration (Chu & Evans, 2021), which in turn is reflected in the distinct patterns of interdisciplinarity and temporal diversity across fields.

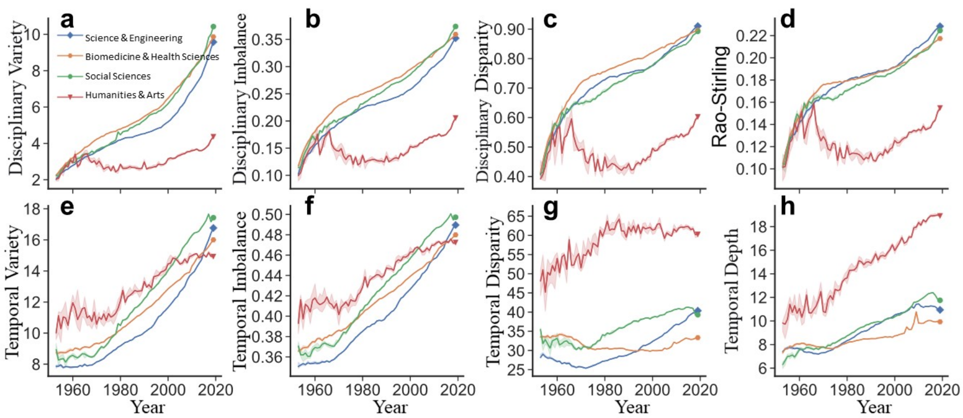

Figure 2. Temporal Trends in Interdisciplinarity and Temporal Diversity Across Different Fields

Note: The shaded areas represent the 95% confidence intervals.

3.3 Distribution and Interrelationship between Interdisciplinarity and Temporal Diversity

The measurement frameworks for interdisciplinarity and temporal diversity in this study comprise eight specific indicators. Understanding the distribution characteristics and interrelationships of these indicators is therefore of particular importance. To this end, this paper analyzes the probability distributions of the interdisciplinarity and temporal diversity indicators across 38,879,575 papers, with the results presented in Fig. 3a-h.

As defined in Section 3.1, four indicators—*disciplinary variety, temporal variety, temporal disparity*, and *temporal depth*—can be treated as count variables. The results indicate that their distribution characteristics conform to a scale-free power-law pattern. The distributions of these four indicators were fitted using a power-law function, $N(x) \sim kx^{-\gamma}$ with the fitted γ values all being relatively large. In contrast, indicators such as disciplinary imbalance, the Rao-Stirling index, and temporal imbalance exhibit characteristics of log-normal distributions, with values mostly concentrated around the median. These results demonstrate that neither the interdisciplinarity nor the temporal diversity indicators are uniformly distributed; instead, they exhibit pronounced heterogeneous distribution patterns.

Figures 3-i present the interrelationships between the indicators of interdisciplinarity and temporal diversity, where each point represents one of the 292 subfields in the Microsoft Academic Graph. The Pearson correlation coefficient between temporal variety and disciplinary variety is 0.63, and that between temporal imbalance and disciplinary imbalance is also 0.47, indicating a moderately strong positive correlation for these two pairs of variables. In contrast, the Pearson correlation coefficient between temporal disparity and disciplinary disparity is 0.11, while that between the Rao-Stirling index and temporal depth is -0.02, both showing very weak correlations. These findings indicate that although the indicators for interdisciplinarity and temporal diversity are constructed based on analogous conceptual frameworks and exhibit similar temporal trends, the correlations between them are not particularly strong.

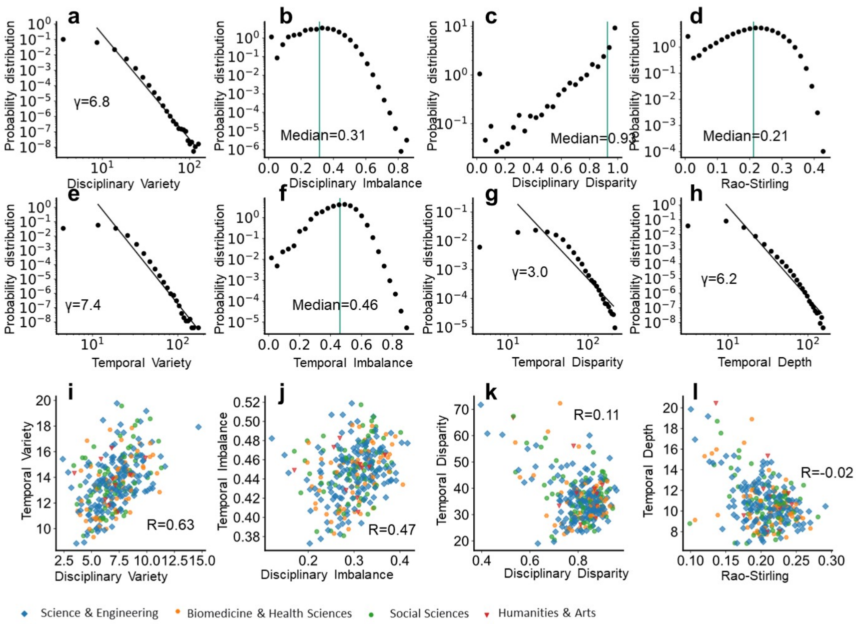

Figure 3. Distribution Characteristics and Interrelationships of Interdisciplinarity and Temporal Diversity

Note: In panels i-j, each point represents one of the 292 MAG subfields.

3.4 Evolution of Interdisciplinarity and Temporal Diversity over Scientific Careers

To further understand the evolutionary mechanisms of interdisciplinarity and temporal diversity, this section analyzes these aspects at the level of individual scientific careers. Prior research has shown that, over the course of a complete scientific career, the distribution of a scientist's paper impact is relatively random (Liu et al., 2018; Sinatra et al., 2016), while their collaboration patterns and research topics often evolve (Zeng et al., 2019, 3439). However, the patterns of how interdisciplinarity and temporal diversity evolve over a scientist's career remain unclear. Furthermore, analysis at the author level helps control for selection bias.

To mitigate the influence of factors such as incomplete career data and high-impact co-authors on the measured interdisciplinary and temporal characteristics of scientists (Petersen et al., 2014), this section focuses solely on highly productive scientists. Since the author's name disambiguation in the Microsoft Academic Graph performs less reliably for authors with extremely high publication volumes, to ensure data quality, this study selected a sample of 119,880 highly productive scientists who have published between 100 and 200 papers within the dataset.

Considering all N papers published by scientist a during their career, this study first arranges them chronologically by publication date to obtain the real career paper sequence, $I_a(real)$. Concurrently, for each scientist, the career paper sequence is randomly reshuffled multiple times to generate a series of random career paper sequences, $I_a(random)$, which serve as a null model. In Figures 4a-h, the green line represents the evolution of indicator values for each paper $i(real)$ in the real career sequence $I_a(real)$, plotted against the paper's order in the sequence. The black line represents the same for each paper $i(random)$ in the null model's random sequence$I_a(random)$. The results show significant increasing trends across all eight interdisciplinarity and temporal diversity indicators over the course of a scientist's real career, whereas no clear career-long trend is observed in the null model.

Simultaneously, an increasing trend in the number of references per paper over a scientist's career is also observed (Fig. 4q). This indicates a tendency for scientists to cite an increasing volume of literature throughout their careers, which is likely to influence interdisciplinarity and temporal diversity. To address this, the analysis controls for the number of references by examining the evolution of indicators specifically for papers with the same reference count. The results, shown in Figs. 4i-p, demonstrate that after controlling for the number of references, the increasing trends in scientists' interdisciplinarity and temporal diversity are significantly attenuated. This suggests that the marked growth in interdisciplinarity and temporal diversity observed over a scientist's career can be largely attributed to the increase in the number of references in their papers. Notably, this effect is most pronounced for the variety indicators but does not hold for temporal depth, which reflects the age of references.

This study further analyzes the trend in paper impact over a scientist's career, as shown in Fig. 4r.

The vertical axis represents paper impact using the normalized citation count $C_{f,t}$, defined as a paper's raw citation count divided by the average citation count of papers published in the same year and field. This method effectively accounts for issues related to the citation time window and field heterogeneity (Radicchi et al., 2008). The results in Fig. 4r indicate no significant difference in paper impact between the real data and the random null model, reflecting that paper impact is relatively random over a scientist's career. This finding aligns with existing research conclusions (Liu et al., 2018; Sinatra et al., 2016). For instance, Liu et al. found that the impact of papers within a scientist's career can be modeled by a multi-stage normal distribution.

These findings prompt a new research question: *If paper impact is relatively random over a scientist's career, while interdisciplinarity and temporal diversity exhibit growth patterns modulated by citation practices, what is the relationship between interdisciplinarity, temporal diversity, and paper impact?* The following section will construct fixed-effects regression models to investigate this question.

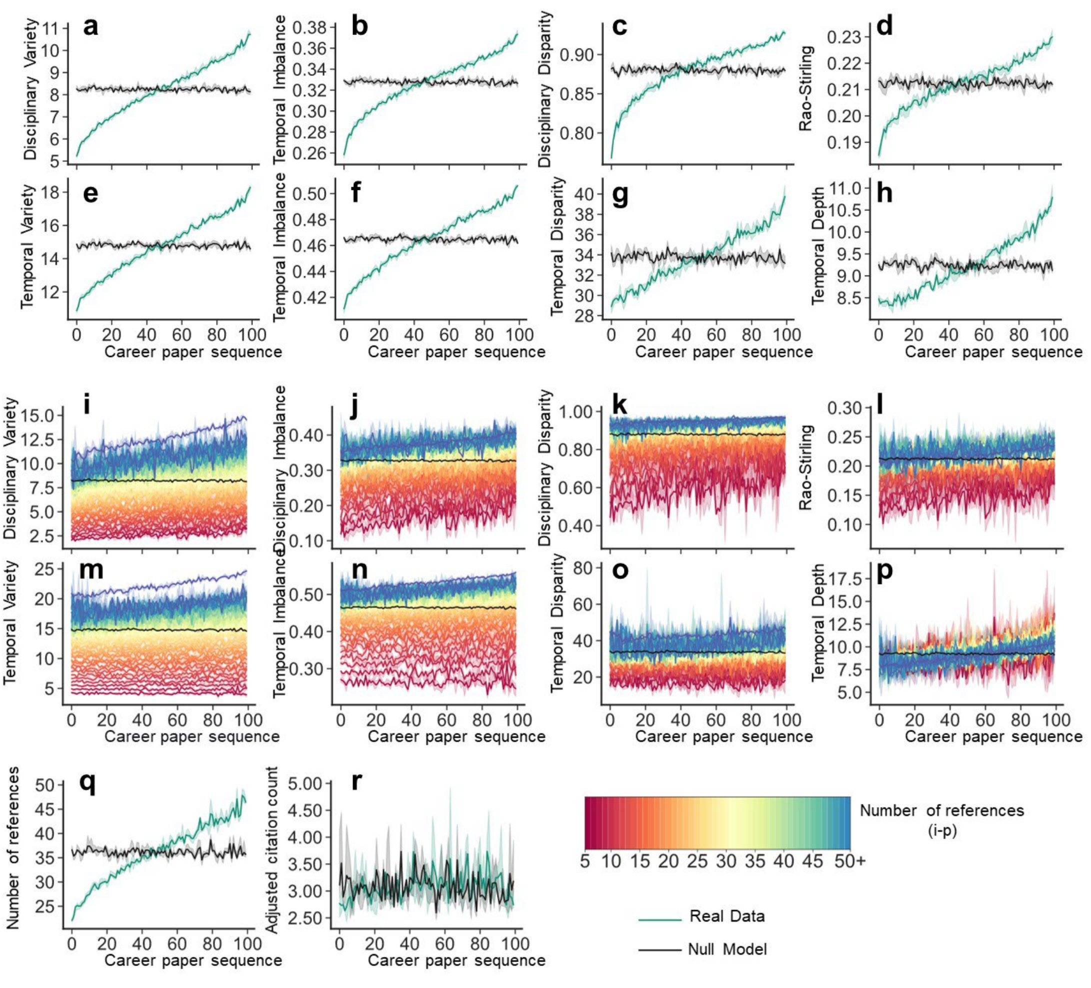

Figure 4. Scientist-Level Career Evolution Patterns of Interdisciplinarity and Temporal Diversity

Note: The shaded areas indicate 95% confidence intervals.

4. Interdisciplinarity, Temporal Diversity, and Paper Impact

4.1 Variable Description and Empirical Model

Given its high interpretability, the raw citation count of a paper serves as the primary measure of scientific impact in this study. Citation counts reflect the degree of recognition and contribution share a paper receives within the academic community (Alex Jie Yang, Linwei Wu, et al., 2023, 101456). However, raw citation counts are also influenced by factors such as field, publication year, and the citation time window. This study employs fixed-effects models to mitigate their influence on the regression results. Furthermore, as raw citation counts typically follow a long-tailed distribution, they are transformed using the natural logarithm for the analysis.

This study also constructs a higher-order indicator ***Disruptive Hit Papers***, to capture a paper's disruptive impact and overall influence, integrating the two dimensions of disruptiveness and academic impact. The *disruptiveness* index is an innovation metric proposed by Funk and Owen-Smith (Funk & Owen-Smith, 2017). From the perspective of the citation network, it assesses the degree to which a paper alters the structure of the scientific network. If subsequent papers citing a Focal Paper (*FP*) also cite FP's references, then *FP* is considered to consolidate the existing knowledge paradigm. Conversely, if future citations reference only FP itself and ignore its foundational references, they acknowledge FP's disruptive value. The disruptiveness index is defined as:

$$CDindex = p_D - p_C = \frac{n_{DC} - n_{CC}}{n_{DC} + n_{CC} + n_{RC}} \tag{5}$$

Here, n_{CC}, n_{DC}andn_{RC}represent the number of papers that cite both FP and its references, cite FP but not its references, and cite FP's references but not FP itself, respectively.

A higher CD index indicates a paper that disrupts its local knowledge structure, while a lower index suggests the paper consolidates the established paradigm (Alex Jie Yang, Sanhong Deng, et al., 2023, 101411).Given certain limitations of the CD index, such as uneven distribution and measurement inaccuracies (Leibel & Bornmann, 2023; Alex J. Yang et al., 2023; Alex J. Yang et al., 2024), this study dichotomizes it using 0 as the threshold. Building on this, a ***Disruptive Hit Paper*** is defined as a Hit Paper (i.e., a paper whose citation count ranks in the top 10% within its field and publication year) with a CD index greater than 0. This definition combines scientific impact and disruptiveness, providing a more precise reflection of a paper's disruptive influence. In our dataset, only 1.9% of papers are classified as Disruptive Hit Papers. Notably, these Disruptive Hit Papers account for over three-quarters of the Nobel Prize-winning papers within the dataset.

To account for the influence of confounding factors on a paper's interdisciplinarity, temporal diversity, citation count, and other characteristics, this study incorporates the following control variables: (1) the number of references (Alex J. Yang et al., 2024); (2) the scale of team collaboration, i.e., the number of co-authors (Jones et al., 2008); (3) whether the collaboration is international(Jones et al., 2008); (4) whether the team is interdisciplinary (Lin et al., 2023); (5) the team's mean academic age (Liu et al., 2018); (6) the team's mean publication count up to the paper's publication year (Liu et al., 2018); (7) whether the research received funding from agencies such as the NIH or NSF (Yang, 2024); (8) year fixed effects (Park et al., 2023) for the period 1950-2020; (9) field fixed effects (Chu & Evans, 2021) based on the 292 subfields; and (10) journal fixed effects (covering 39,893 journals).

To analyze the effects of interdisciplinarity and temporal diversity on paper impact, this study employs an OLS regression model:

$$Citation_{iyfj} = \alpha + \beta_1(Diversity_i) + \beta_2(Controls) + Y_t + F_i + J_i + \epsilon_{iyfj} \tag{6}$$

Here, i denotes the paper, y its publication year, f its field, and j its journal. The model includes three-way fixed effects for year, field, and journal. This specification controls for time trends (Park et al., 2023), field-specific distributions (Chu & Evans, 2021), and variations in paper type and subject matter, thereby enabling a more accurate estimation of the effects of interdisciplinarity and temporal diversity on paper impact.

4.2 Interdisciplinarity, Temporal Diversity, and Paper Citation Count

Table 1 presents the OLS regression results examining the effects of interdisciplinarity indicators on paper citation counts. After controlling for confounding factors including the number of references, team size, team mean academic age, team publication count, international collaboration, interdisciplinary collaboration, funding status, as well as three-way fixed effects for year, field, and journal, the analysis reveals that disciplinary variety, disciplinary disparity, and the Rao-Stirling index all have a significant positive effect on paper citation counts. In contrast, disciplinary imbalance exhibits a significant negative effect on citations.

Specifically, a one-unit increase in disciplinary variety is associated with a 0.25% rise in citation count; a one-unit increase in disciplinary disparity corresponds to a 6.24% increase in citations; a one-unit increase in the Rao-Stirling index leads to a 7.75% increase in citations; while a one-unit increase in disciplinary imbalance results in a 6.1% decrease in citations. To further interpret these effects based on the standard deviations of the variables: a one-standard-deviation increase in disciplinary variety promotes a 1.15% (0.25% × 4.61)increase in citations; a one-standard-deviation increase in disciplinary disparity promotes a 1.86% (6.24% × 0.24) increase; a one-standard-deviation increase in the Rao-Stirling index promotes a 0.62% (7.75% × 0.08) increase; and a one-standard-deviation increase in disciplinary imbalance leads to a 0.73%(6.1% × 0.12) decrease in citations.

Model	(1) ln (citation count)	(2) ln (citation count)	(3) ln (citation count)	(4) ln (citation count)
Disciplinary variety	0.0025*** (6e-5)			
Disciplinary imbalance		0.0610***		
		(0.0018)		
Disciplinary disparity			0.0624***	
			(0.0009)	
Rao-Stirling				0.0775***
				(0.0024)
ln (References)	0.5115***	0.5169***	0.5137***	0.5198***
	(0.0004)	(0.0003)	(0.0003)	(0.0003)
ln (Team size)	0.1937***	0.1935***	0.1934***	0.1937***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
ln (Academic age)	-0.0577***	-0.0579***	-0.0580***	-0.0581***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
ln (Publication count)	0.0911***	0.0911***	0.0911***	0.0912***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
International collaboration	0.0315***	0.0318***	0.0319***	0.0317***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Interdisciplinary collaboration	-0.0342*** (0.0004)	-0.0338*** (0.0004)	-0.0340*** (0.0004)	-0.0339*** (0.0004)
Funding support	0.1368***	0.1372***	0.1376***	0.1372***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Journal FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Field FE	Yes	Yes	Yes	Yes
Observations	38,469,142	38,469,142	38,469,142	38,469,142
R^2	0.4974	0.49739	0.49745	0.49739

Table 1. OLS Regression Results of Interdisciplinarity Indicators on Paper Citation Counts

*Note: All models are estimated using OLS regression. Robust standard errors are reported in parentheses. The results presented here include all control variables; the conclusions remain consistent if certain controls or fixed effects are excluded. Significance levels: *p < 0.05, **p < 0.01, ***p < 0.001.*

Table 2 presents the OLS regression results examining the effects of temporal diversity indicators on paper citation counts. After controlling for confounding factors including the number of references, team size, team mean academic age, team publication count, international collaboration, interdisciplinary collaboration, funding status, as well as three-way fixed effects for year, field, and journal, the analysis reveals that temporal variety, temporal imbalance, temporal disparity, and temporal depth all have a significant negative effect on paper citation counts. To interpret the effects based on the standard deviations of the variables: a one-standard-deviation increase in temporal variety leads to a 15.5% (2.62% × 6.87) decrease in citations; a one-standard-deviation increase in temporal imbalance results in a 0.26% (2.62% × 0.10) decrease; a one-standard-deviation increase in temporal disparity causes a 2.77% (0.12% × 23.06) decrease; and a one-standard-deviation increase in temporal depth is associated with an 11.2% (1.95% × 5.74) decrease in citations.

These findings demonstrate that the effect of temporal diversity on paper impact is diametrically opposed to that of interdisciplinarity: while the interdisciplinarity of scientific knowledge significantly promotes paper citation counts, the temporal diversity of scientific knowledge significantly suppresses them.

Model	(1) ln (citation count)	(2) ln (citation count)	(3) ln (citation count)	(4) ln (citation count)
Temporal variety	-0.0262***			
	(4.81e-5)			
Temporal imbalance		-1.539***		
		(0.0031)		
Temporal disparity			-0.0012***	
			(7.95e-6)	
Temporal depth				-0.0195***
				(3.35e-5)
ln (References)	0.7317***	0.6792***	0.5355***	0.5225***
	(0.0005)	(0.0004)	(0.0003)	(0.0003)
ln (Team size)	0.1859***	0.1938***	0.1912***	0.1829***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
ln (Academic age)	-0.0355***	-0.0369***	-0.0543***	-0.0264***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
ln (Publication count)	0.0798***	0.0796***	0.0895***	0.0729***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
International collaboration	0.0338***	0.0307***	0.0323***	0.0325***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Interdisciplinary collaboration	-0.0322*** (0.0004)	-0.0319*** (0.0004)	-0.0328*** (0.0004)	-0.0325*** (0.0004)
Funding support	0.1388***	0.1376***	0.1369***	0.1370***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Journal FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Field FE	Yes	Yes	Yes	Yes
Observations	38,469,142	38,469,142	38,469,142	38,469,142
R^2	0.50159	0.5013	0.49767	0.50231

Table 2. OLS Regression Results of Temporal Diversity Indicators on Paper Citation Counts

*Note: All models are estimated using OLS regression. Robust standard errors are reported in parentheses. The results presented here include all control variables; the conclusions remain consistent if certain controls or fixed effects are excluded. Significance levels: *p < 0.05, **p < 0.01, ***p < 0.001.*

4.3 Interdisciplinarity, Temporal Diversity, and Disruptive Hit Papers

To analyze the combined effect of the horizontal distribution characteristic (interdisciplinarity) and the vertical distribution characteristic (temporal diversity) of the knowledge base on scientific disruptive impact, this study classifies each indicator of interdisciplinarity and temporal diversity into quantiles. The probability distribution of Disruptive Hit Papers across the binary combinations of interdisciplinary and temporal diversity features is then calculated, with the results presented in Figure 5.

The findings elucidate the underlying mechanism through which interdisciplinary and temporal diversity characteristics influence scientific disruptive impact: The high-probability space for Disruptive Hit Papers is located where temporal variety, temporal imbalance, temporal disparity, and the Rao-Stirling index are relatively low, while simultaneously where disciplinary variety, disciplinary disparity, and the Rao-Stirling index are relatively high. A paper combining weaker temporal diversity with stronger interdisciplinarity has the highest probability of becoming a Disruptive Hit Paper.

Thus, the horizontal dispersion and vertical focus of the knowledge base are key to generating breakthrough research. In the vertical dimension, a recent and focused knowledge base helps enhance a paper's impact. In the horizontal dimension, integrating knowledge from multiple disciplines can significantly increase a paper's impact. Disruptive, high-impact research often requires building upon cutting-edge knowledge foundations rather than relying on older ones—truly "standing on the shoulders of giants." Furthermore, interdisciplinary knowledge integration is crucial for boosting scientific impact. The organic combination of horizontal expansion and vertical convergence of scientific knowledge can give rise to more high-impact research outcomes.

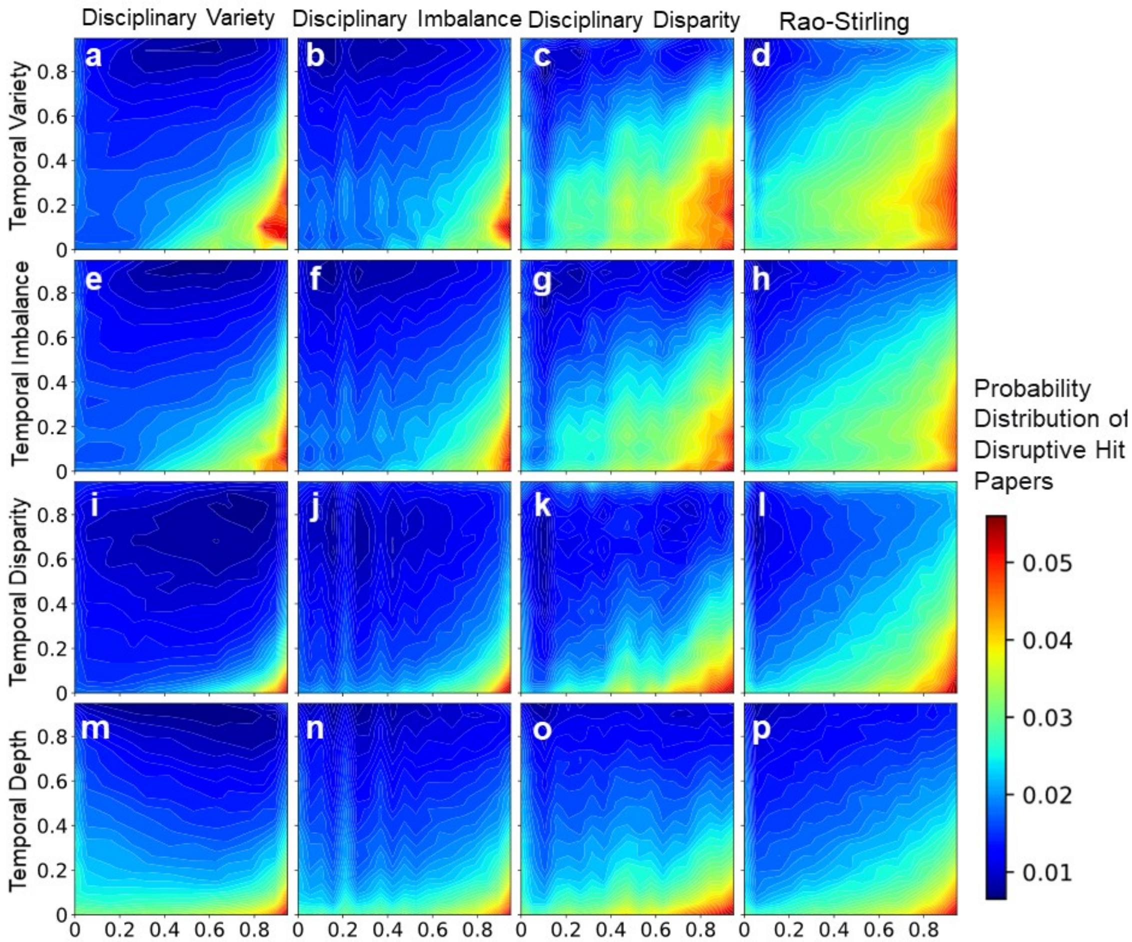

Figure 5. Probability Distribution of Disruptive Hit Papers across Interdisciplinarity and Temporal Diversity

Note: The values on both the horizontal and vertical axes are linearly mapped to quantiles.

5. Conclusion and Outlook

This study, through an analysis of the horizontal and vertical dimensions of the knowledge base of 38,879,575 papers published between 1950 and 2020 from the Microsoft Academic Graph, investigates the temporal trends, disciplinary variations, distribution characteristics, interrelationships, and patterns across scientists' careers concerning interdisciplinarity and temporal diversity. Building on this foundation, it further explores the complex relationship between interdisciplinarity, temporal diversity, and scientific impact.

This research and its findings hold significant theoretical implications. First, building upon the concept of interdisciplinarity, this study proposes a theory and measurement framework for temporal diversity, quantifying a paper's temporal diversity into four dimensions: *temporal variety, temporal imbalance, temporal disparity*, and *temporal depth.* The theory of temporal diversity enriches the measurement frameworks and methodologies within the field of science of science and provides new avenues for research in academic evaluation. The temporal diversity research framework not only extends and complements existing measurement theories but also represents the first systematic framework for measuring the longitudinal distribution of a paper's references, thereby addressing a gap in current research on the vertical dimension of scientific knowledge. Second, based on large-sample empirical analysis, this study examines the trends and characteristics of the scientific knowledge base: both interdisciplinarity and temporal diversity exhibit increasing temporal trends, reflecting both the growing integration of specialized knowledge and the potential negative effects of knowledge overload on future innovation (Chu & Evans, 2021; Jones, 2009). Indicators such as interdisciplinarity and temporal diversity show heterogeneous distribution patterns, notably scale-free power-law distributions, and are not strongly correlated with each other, enriching the understanding of these indicators. Over the course of a scientist's career, both interdisciplinarity and temporal diversity show significant growth trends, largely attributable to the increase in the number of references per paper. This finding reveals evolutionary patterns at the scientist level and enriches the relevant field.

The findings of this study also possess practical significance. The interdisciplinarity of scientific knowledge promotes paper impact, while temporal diversity tends to suppress it. This conclusion provides valuable guidance for researchers when planning research directions and selecting knowledge foundations. Furthermore, this study finds that ***Disruptive Hit Papers*** possess a knowledge base characterized by horizontal dispersion and vertical focus; younger knowledge foundations are more likely to generate high-impact, even disruptive research. Consequently, policymakers should encourage researchers to engage in cutting-edge, interdisciplinary research projects and provide increased funding for such endeavors. An interdisciplinary knowledge base positively influences research impact, which can be promoted by encouraging interdisciplinary collaboration, supporting diverse research teams, and providing relevant research opportunities.

This study also has several limitations. First, it analyzes only the correlation between interdisciplinarity, temporal diversity, and scientific impact, without delving into causal effects. Second, it treats all citations as consistent, without considering issues of invalid citations or citation polarity (Bao & Teplitskiy, 2024). Third, scientific impact and innovation are complex and multifaceted; this study analyzes them only from the perspectives of citation counts and disruptiveness, neglecting other dimensions such as societal impact. Fourth, it assumes that papers across all disciplines conform to the "paradigm shift" theory of innovation (Kuhn, 1962); however, this theory may not hold for humanities and social sciences. Perspectives based on theories like "paradigm alternation"(Zhao, 2015) could yield more precise conclusions for these fields.

Future research could employ quasi-experimental methods to investigate the causal mechanisms linking interdisciplinarity, temporal diversity, and scientific impact. It could also consider heterogeneous types of scientific innovation, conducting fine-grained analyses of mechanisms specific to different fields. Furthermore, while this study focuses on analyzing interdisciplinarity and temporal diversity based on a paper's references, future work could employ finer-grained measurement methods, such as extracting patterns of knowledge integration from text or topics. It could also integrate the backward flow of knowledge, analyzing the broader impact mechanisms of the interdisciplinarity and temporal diversity of the knowledge base on the entire scientific system based on citation cascades.

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