Postprint: A Study on the Impact Breadth of Academic Papers Based on Innovation Diffusion Theory

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Abstract

[Purpose/Significance] Using citation count to measure academic paper impact has numerous limitations. This paper argues that academic paper impact encompasses three aspects: depth, speed, and breadth of dissemination, and that entropy can be employed to measure the breadth of impact dissemination. [Method/Process] Nobel Prize papers in the biomedical field from 1901-2017 were selected as the most influential papers for the experimental group, and a control group was established according to a 1:1 matching principle. The number of disciplines of citing literature, entropy values, and the correlation between entropy and citation count within five years post-publication were compared between the two groups. [Results/Conclusion] In the experimental group, over 65% of papers exhibited a higher number of disciplines in their citing literature compared to the control group; the mean entropy of the experimental group ranged from 0.552-0.772, while that of the control group ranged from 0.251-0.481, with statistically significant differences (P<0.05); the correlation between citation count and entropy was weak for both groups, each being less than 0.3. The results indicate: Over 70% of high-impact papers can influence multiple disciplines in the early period following publication; Using entropy to identify the breadth of paper impact is feasible.

Full Text

Preamble

Impact Breadth of Scientific Papers Based on Innovation Diffusion Theory

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Abstract

[**Purpose/Significance**] Using citation counts to measure the impact of academic papers has numerous drawbacks. This study argues that the impact of a scientific paper comprises three dimensions: depth, speed, and breadth of its diffusion. Entropy can be employed to measure the breadth of a paper's impact diffusion. [**Method/Process**] Nobel Prize-winning papers in biomedicine from 1901–2017 were selected as the most influential papers for the experimental group, with a control group established according to a 1:1 matching principle. We compared the number of disciplines spanned by citing documents, entropy values, and the correlation between entropy and citation counts within five years after publication for both groups. [**Result/Conclusion**] Over 65% of papers in the experimental group had higher disciplinary diversity in their citing documents than the control group. The mean entropy values ranged from 0.552–0.772 for the experimental group and 0.251–0.481 for the control group, showing significant differences ($P < 0.05$). The correlation between citation counts and entropy was weak in both groups, all below 0.3. The results indicate that: (1) more than 70% of highly influential papers impact numerous disciplines in their early publication years; (2) using entropy to identify the impact breadth of papers is feasible.

Keywords: innovation diffusion; entropy; Nobel Prize papers; biomedicine

1. Introduction

Innovation diffusion theory, proposed by American scholar Everett Rogers (E.M. Rogers) in the 1960s, explains how, why, and at what speed new ideas spread through populations [1]. Rogers defined diffusion as "the process by which an innovation is communicated through certain channels over time among members of a social system," with four key elements: innovation, communication channels, time, and social system. The most important characteristics promoting diffusion include high comparative advantage, compatibility, trialability, observability, and low complexity.

What constitutes diffusion? Rogers viewed it as the intentional or unintentional spread of new ideas. Wikipedia defines diffusion as the net movement of molecules or atoms from regions of high concentration to low concentration until uniform distribution is achieved, encompassing three dimensions: depth, breadth, and speed [2]. Breadth—width or horizontal distance—measures the extent of spread. In graph theory, the breadth-first algorithm exemplifies this by starting from a root node and locating all nodes at distance 1 (maximum breadth), iterating until termination [3]. Depth represents downward or inward distance, as seen in depth-first algorithms that search as deeply as possible along connected nodes [3]. Speed reflects how fast something moves, defined in physics as the rate of change of displacement with respect to time [4].

In academic networks, each peer-reviewed paper carries new ideas and knowledge, with citations recording the flow of these ideas [5–7]. The dynamic changes in citation counts after publication can be viewed as an innovation diffusion process, allowing paper impact to be decomposed into depth, breadth, and speed [8–10]. The speed of impact diffusion primarily manifests in the time required to reach a certain citation count after publication. For instance, if Papers A and B both achieve n citations, but Paper A reaches n in 3 years while Paper B takes 10 years, Paper A's impact diffuses faster. Depth reflects the number of citation cascades—chains where a paper is cited by subsequent papers, which are themselves cited, forming a directed acyclic citation network [11]. Breadth reflects the extent to which a paper influences research fields beyond its own discipline [10]. For example, if Papers C and D published in the same year have equal citations after n years, but Paper C's citing documents span far more disciplines than Paper D, Paper C has greater impact breadth. These three dimensions collectively constitute paper impact, and none can be omitted.

Citation relationships form the basic unit for studying knowledge flow between journals and disciplines. Based on the assumption that researchers cite papers that influence them, numerous scholars have examined scientific knowledge diffusion across disciplines [10, 12–16]. Van Leeuwen and Tijssen [17] argued that scholars disseminate their findings through scientific publications, with citations enabling the tracking of knowledge flows that typically spread first within a field before diffusing to adjacent disciplines. Yan [18] studied knowledge creation and diffusion across 27 disciplines in Scopus, using information entropy to analyze citation diversity and found that chemical engineering, energy, and environmental science had the fastest-growing influence, with most fields showing high citation diversity—indicating strong interdisciplinary influence. Zhai et al. [10] analyzed LDA technology diffusion across disciplines from 2003–2015, revealing that it spread first to neighboring fields before reaching others, gradually being supplemented and developed. Thus, whether and to what extent an academic idea diffuses across disciplines reflects its impact breadth.

Based on innovation diffusion theory, this study explores the impact breadth of scientific papers, proposing that the disciplinary diversity of citing documents can measure this breadth. Nobel Prizes represent the highest honor in science, and Nobel-winning papers are among the most influential and innovative. Therefore, we collected representative Nobel-winning papers in biomedicine from 1901–2017 as our experimental group, with a matched control group for comparison. This paper first describes data acquisition for both groups, methods for calculating disciplinary diversity and impact breadth, then analyzes disciplinary diversity, impact breadth, correlations between entropy and citations, and the feasibility of using entropy for measurement, concluding with discussion and summary.

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2. Data Sources and Methods

2.1 Data Sources

From 1901–2017, 214 researchers received Nobel Prizes in biomedicine. Based on the Nobel Committee's laureate list, award years, and citations, we extracted names, award years, and award topics. For each laureate, we identified their two most-cited papers related to the award topic published before receiving the prize. For example, H. Dam received the 1943 Nobel Prize in Physiology or Medicine for discovering vitamin K. We used "Vitamin K" as the search term to retrieve Dam's most-cited two journal papers published before 1943. However, not all laureates had such clear search terms. For Karl Landsteiner, awarded in 1930 for discovering the ABO blood group system, we obtained personal information from Wikipedia and used "blood," "antigen," "serum," and "serology" as keywords to retrieve his two most-cited pre-1930 papers. Ultimately, we obtained 389 Nobel papers and 67,724 citing documents within five years after publication for the experimental group.

The control group used a 1:1 matched design, randomly selecting non-Nobel papers in the same field published before the laureate's award year and on the same research topic. For H. Dam's Nobel papers, we searched WoS for pre-1943 papers on "Vitamin K" by other researchers, randomly selecting two as controls. This yielded 389 non-Nobel papers and 17,353 citing documents within five years after publication. All data came from the Web of Science (WoS) database.

2.2 Methods

2.2.1 Calculating Disciplinary Diversity of Citing Documents Following Clarivate Analytics' disciplinary classification, science is divided into six broad categories: Arts & Humanities, Clinical/Pre-clinical & Health (Medicine), Engineering & Technology, Life Sciences, Physical Sciences, and Social Sciences, comprising 256 sub-disciplines [19]. The algorithm calculates how many citing disciplines fall outside the paper's own field. All medical sub-disciplines were scored 0, non-medical sub-disciplines 1. The cumulative score for each paper's citing documents within five years after publication was calculated using Formula (1):

$$S_i = \sum_{j=1}^{n} x_{ij}$$

where S_i is the cumulative disciplinary score for paper i, n is the number of disciplines spanned, and x_{ij} is the score for paper i's jth sub-discipline. If the sub-discipline is non-medical $(D - D_{medicine})$, $x_{ij} = 1$; if medical $(D_{medicine})$, $x_{ij} = 0$. Duplicate disciplinary classifications were not double-counted. With 47 medical sub-disciplines, the maximum possible score is 209 (256 total minus 47 medical sub-disciplines).

2.2.2 Calculating Impact Breadth Entropy, derived from the second law of thermodynamics, measures system disorder—higher disorder yields higher entropy. In 1948, Shannon introduced entropy to information theory as a measure of uncertainty or information content for random events, with maximum entropy when probabilities are equal [20]. In academic networks, disciplinary diversity can be measured using entropy [20]. This study uses the proportion of each discipline among a paper's citing documents as conditional probability $p(j)$. When paper j belongs to only one GIPP sub-discipline, its entropy is the ratio of each sub-discipline's citations to total citations. When paper j spans multiple disciplines, its entropy is the mean entropy across all its sub-disciplines. If citing documents belong to $ $1 discipline, entropy = 0. Theoretically, higher disciplinary diversity yields higher entropy. The entropy formula is:

$$H(j) = -\sum_j p_j \cdot \log(p_j)$$

where $H(j)$ is paper j's entropy and p_j is the conditional probability (proportion of citations from discipline j).

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3. Results

3.1 Disciplinary Distribution of Citing Documents

3.1.1 Cumulative Disciplinary Distribution Figure 2 [Figure 2: see original paper] shows the yearly cumulative number of disciplines spanned by citing documents for both groups within five years after publication. Both groups show increasing trends, with the experimental group consistently higher than the control group.

3.1.2 Distribution of Disciplinary Counts and Paper Volume To further examine the relationship between disciplinary span and paper volume, we analyzed the number of papers corresponding to different disciplinary counts. As shown in Figure 3 [Figure 3: see original paper], the experimental group had more papers spanning five or more disciplines. Detailed analysis revealed that in each of the first five years post-publication, over 65% of experimental group papers had higher disciplinary diversity than their matched controls: 253

papers (65.04%) in year 1, 251 (64.52%) in year 2, 261 (67.10%) in year 3, 265 (68.12%) in year 4, and 267 (68.64%) in year 5.

3.2 Impact Breadth of Both Groups

This study measures impact breadth through disciplinary diversity of citing documents, applying entropy to calculate this diversity. As Figure 4 [Figure 4: see original paper] illustrates, mean entropy values increased annually from year 1 to 5 post-publication. The experimental group's entropy ranged from 0.552–0.772, while the control group's ranged from 0.251–0.481. U-tests showed significantly higher entropy in the experimental group ($p < 0.05$). Specifically, in years 1–5, the experimental group had higher entropy than controls in 273 (70.36%), 268 (69.07%), 274 (70.62%), 276 (71.13%), and 276 (71.13%) papers, respectively.

3.3 Correlation Between Citations and Entropy

Using entropy to measure impact breadth should not reflect citation counts. To assess potential citation effects, we examined correlations between entropy and citation counts. Results showed weak, decreasing correlations from year 1 to 5: experimental group correlations were 0.280, 0.235, 0.199, 0.176, and 0.161; control group correlations were 0.240, 0.143, 0.109, 0.094, and 0.078—all below 0.3 (Figure 6 [Figure 6: see original paper]).

3.4 Feasibility of Using Entropy to Measure Impact Breadth

If experimental group papers have higher entropy than controls, they should also show higher disciplinary diversity, and vice versa. We therefore analyzed the consistency between entropy differences and disciplinary count differences between groups. Results showed consistent directional changes in 77.84%, 55.67%, 75.26%, 75.00%, and 73.97% of cases from years 1–5, respectively (Table 1).

Table 1 Comparison of Entropy and Sub-disciplinary Counts Between Groups

Year	Experimental > Control	Experimental = Control	Experimental < Control
Year 1	77.84%	11.08%	11.08%
Year 2	55.67%	29.41%	14.92%
Year 3	75.26%	12.37%	12.37%
Year 4	75.00%	12.50%	12.50%
Year 5	73.97%	13.01%	13.01%

4. Discussion

In the context of innovation-driven development, fair and objective evaluation of academic paper impact helps administrators and policymakers grasp frontier achievements, maximizes limited resources to advance science, and affects researchers' career advancement, compensation, and funding—thereby influencing their motivation.

As early as 1927, P.L. Gross and E.M. Gross from Pomona College used citation counts to assess research importance when discussing chemistry education and university library development [21]. Since then, citation analysis has been widely applied in national science policy, disciplinary development, research groups, journals, individuals, and paper evaluation [22–24]. For example, OECD uses top 10% most-cited papers to evaluate national research performance, finding China's share rose from <4% in 2005 to 14% in 2016, ranking second globally [25]. Since 2013, Clarivate Analytics' annual *Research Fronts* report has used top 1% most-cited papers to identify hotspots in natural and social sciences. However, academic networks are dynamic, self-organizing, and complex. Using cumulative citations to measure impact has drawbacks: it disadvantages new papers and suffers from "Matthew effects" [5], and researchers' most-cited works are not necessarily their best [26].

To address these limitations, scholars have developed numerous metrics from h-index [27] to g-index [28], impact factor [29] to Eigenfactor [30]. While these citation-based indicators have improved evaluation, limitations remain. H-index and g-index, though balancing quantity and citation impact, are unsuitable for evaluating early-career scientists. Impact factor, designed for journal selection, is now widely used for paper quality evaluation but is affected by article type and research field, with papers in the same journal showing divergent citation patterns over time. Eigenfactor, borrowing PageRank principles to weight high-impact citations, emphasizes quality and yields article influence scores, but offers poor discrimination for lower-impact journals and involves complex calculations [31].

Based on innovation diffusion theory, we propose that paper impact comprises three dimensions—depth, speed, and breadth—and that disciplinary diversity of citing documents can measure breadth. Using Nobel-winning papers in biomedicine as high-impact examples and matched non-Nobel controls, we compared disciplinary diversity within five years post-publication to enhance comparability.

Results show that from year 1 to 5 post-publication, over 65% of experimental group papers had higher disciplinary diversity than controls, widely distributed across five or more disciplines. Citation analysis revealed that >70% of experimental papers had higher citation counts than controls, suggesting higher-cited papers tend to have greater disciplinary span. Entropy, measuring system complexity and disorder, can mitigate citation bias. Within five years, experimental group entropy (0.552–0.772) significantly exceeded controls (0.251–0.481, $p < 0.05$), with weak entropy-citation correlations, confirming higher impact breadth in the experimental group. Notably, 28.28%, 26.99%, 24.68%, 23.65%, and 22.62% of high-impact papers had citation counts lower than or equal to controls in years 1–5, with the number of such papers stabilizing around 76

(19.54%). This indicates that early-stage citation counts may not reliably identify high-impact papers, creating potential evaluation bias.

Key conclusions: (1) Over 70% of highly influential papers impact multiple disciplines early on; (2) Entropy is feasible for identifying impact breadth.

Some papers fail to achieve broad impact due to insufficient innovation or, conversely, excessive innovation and complexity that exceeds common understanding, becoming "sleeping beauty" papers [6, 32–33]. Maximum impact often occurs when papers balance innovation with tradition [6, 32–33].

This exploratory study has limitations: (1) Entropy cannot reflect citation magnitude—Papers A and B from medicine cited by arts, medicine, and philosophy would have identical entropy regardless of 100 vs. 10 citations. (2) The study assumes equal similarity between all disciplines, though urology and neuroscience are more similar than urology and linguistics, yet would yield identical entropy values. Future work will incorporate inter-disciplinary similarity for more objective impact comparison and integrate all three impact dimensions for early identification of influential papers.

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Author Contributions

Liang Guoqiang: Conceptualized the study, designed the research framework, collected and analyzed data, wrote the manuscript.
Hou Haiyan: Supervised and revised the manuscript.
Gao Tong: Collected and analyzed data.
Kong Xiangjie: Participated in discussions and refined the research framework.
Hu Zhigang: Supervised the study and served as corresponding author (E-mail: hu_{zhigang}@dlut.edu.cn).

Note: Figure translations are in progress. See original paper for figures.