Postprint: A Study on the Influence of Interdisciplinary Characteristics on the Citation Trajectory of Scientific Literature

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Date: 2023-04-01T00:00:00+00:00

Abstract

[Purpose/Significance] Citation is not merely a static statistical distribution, but also a complex dynamic evolutionary process. Further exploration of citation curve variations and their influencing factors contributes to understanding the literature lifecycle and dynamic evolution of a discipline, while also holding potential value for scientific forecasting and research evaluation. [Method/Process] This study identifies and classifies different types of citation trajectories, investigating the characteristics, temporal distribution, and other information embedded in citation curves. It quantifies the interdisciplinary degree of papers and examines the relationship between interdisciplinary degree and citation trajectories. [Results/Conclusion] Both "persistent" and "temporary" citation patterns exist across different levels of cumulative citations. For highly-cited literature, interdisciplinary degree shows no significant relationship with cumulative citation trends, yet it plays a certain role in distinguishing between "persistent" and "temporary" citations.

Full Text

The Influence of Interdisciplinary Characteristics on Citation Trajectories in Scientific Literature

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Abstract

[**Purpose/Significance**] Citation behavior is not merely a static statistical distribution but also a complex dynamic developmental process. Further exploration of citation curve variations and their influencing factors can help us understand the literature lifecycle and dynamic development of a discipline, while also offering potential value for scientific prediction and research evaluation. [**Method/Process**] This study identifies and classifies different types of citation trajectories, examining their characteristics, temporal distributions, and other information embedded in citation curves. We measure the interdisciplinary degree of papers and investigate the relationship between interdisciplinarity and citation trajectories. [**Results/Conclusion**] Across different cumulative citation levels, two citation patterns exist: "persistent" and "temporary." For highly cited papers, interdisciplinary degree shows no clear relationship with cumulative citation trends, but it does influence the distinction between "persistent" and "temporary" citations to some extent.

Keywords: Citation analysis; Citation curve; Citation pattern; Interdisciplinary characteristics **Classification Number:** G250 **DOI:** 10.13266/j.issn.0252-3116.2020.14.008

1 Introduction

Citation trajectory refers to the temporal trend of citation frequency for a paper after its publication. Traditional static cumulative citation metrics such as journal impact factor and h-index cannot objectively express and measure literature citation levels [?]. Citation trajectories, by examining the historical process of literature being cited, can measure paper quality and reflect influence from a dynamic development perspective [?]. It is generally believed that literature reaches its citation peak 2-6 years after publication, then enters a decline phase [?]. However, actual citation trajectory patterns exhibit significant variation during the citation lifecycle. In 1979, A. Avramescu summarized five types of citation trajectory curves: three classic curves with high, medium, and low peaks; a "genius-type" curve showing monotonic increase; and a "flash-in-the-pan" curve that was initially recognized but suddenly abandoned [?]. Li Jiang et al. fitted citation trajectories of Nobel laureates' papers and identified five patterns that differed from previous research: classic type, exponential growth type, sleeping beauty type, bimodal type, and wave type [?]. When extending the citation time span, scholars have also discovered "sleeping beauty" literature that was neglected at publication but experienced sudden citation surges years later [?], as well as the opposite "flash-in-the-pan" type [?].

Changes in citation trajectories are closely related to the dynamic evolution of citation networks. For individual papers, citation trajectory development may be influenced by various factors including disciplinary differences [?], author characteristics [?], document types [?], paper length [?], and other factors [?]. E. Roldan-Valadez categorized these factors into three types: paper-related factors, journal-related factors, and author-related factors [?]. Among these, the interdisciplinary characteristics of research outcomes not only reflect knowledge flow across disciplines but also often correlate closely with their impact [?]. Existing studies have reached different conclusions about the relationship between interdisciplinary characteristics and citations. J.M. Levitt [?] and S. Kwon [?], studying social science literature, and G. Abramo, studying natural science literature [?], all confirmed a positive correlation between interdisciplinary characteristics and citations. H.S. Bhat simultaneously studied natural and social science literature and similarly found a positive effect of interdisciplinarity on citations [?]. However, I.V. Ponomarev [?] and E.J. Rinia [?], focusing on chemistry and physics respectively, found no significant relationship between interdisciplinary characteristics and citations. Additionally, in studies by J.M. Levitt and M. Thelwall [?] and J. Wang [?], interdisciplinary characteristics showed some negative correlation with citations.

Thus, the influence of interdisciplinary characteristics on citations is highly complex, with diverse research conclusions due to varied measurement indicators and research objects. Moreover, existing research mostly focuses on the impact of interdisciplinarity on cumulative citation levels, rarely exploring the relationship between interdisciplinary characteristics and citation trajectories. Based on this, our study examines literature in the field of "Library and Information Science," analyzing citation trajectory patterns and characteristics from a temporal distribution perspective, and investigating the relationship between interdisciplinary degree and citation trajectories. This can help us better understand knowledge dissemination processes and provide references for predicting citation patterns. Although this paper conducts citation analysis from a library and information science perspective, the analytical framework and methods can be applied and extended to other levels and perspectives (such as journals, institutions, countries, research topics, etc.).

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2 Research Design and Data Collection

Library and information science has certain interdisciplinary characteristics, maintaining affinity with economics, management, computer science, and other disciplines. Therefore, literature in this field receives relatively high citations with sufficient disciplinary diversity for studying interdisciplinary characteristics. This study takes library and information science as the research field, first characterizing the temporal evolution of citation trajectories and classifying different types of citation trajectories through model fitting. On this basis, using the interdisciplinary degree of individual papers as independent variables and citation trajectory types as dependent variables, we examine the relationship between interdisciplinary characteristics and citation patterns.

2.1 Overview of Citation Trajectory Research Methods

Various models including exponential distribution, logistic distribution, Weibull distribution, Gamma distribution, and Beta analysis have been applied to citation curve modeling [?]. To examine the temporal distribution of citation frequencies and different citation patterns, this study adopts Group-Based Trajectory Modeling (GBTM) [?] to classify citation trajectories and study their characteristics. GBTM is a common method in psychology for studying individual behavior dynamics over time. Based on inherent data heterogeneity, it identifies the number and shape of trajectory groups that characterize data trends, assigning individuals to the most appropriate groups. Each group curve is not an exact trajectory of data changes but rather a visual representation that relatively accurately describes individual developmental heterogeneity in the dataset [?].

The modeling process proceeds as follows:

First, the number of groups is determined by gradually increasing group numbers, and the Bayesian Information Criterion (BIC) is used to select the model that best expresses inter-group heterogeneity. The BIC criterion is commonly used to measure model fit quality while considering model parsimony. To address overfitting caused by increased model complexity and excessive model complexity caused by high precision with large sample sizes, BIC introduces a penalty term related to the number of model parameters while considering sample size: BIC = -2ln(L) + kln(n), where L is the log-likelihood value, k is the number of parameters, and n is the sample size. A BIC value closer to 0 indicates better model fit.

After determining the number of trajectory groups, the curve fitting shape is determined based on experience combined with actual data conditions. From citation patterns, most journal articles reach citation peaks 2-3 years after publication [?], after which citation counts gradually decline and stabilize. Therefore, in this study, all groups initially used cubic polynomial equations, which were gradually adjusted during analysis based on curve results and other indicators.

After determining group numbers and curve equations, model accuracy is verified using average posterior probabilities (APP) for each group. For a model with K groups, each article has L corresponding posterior probabilities. According to the principle of maximum probability grouping, each article is assigned to the corresponding group, and the average of these posterior probabilities for all articles in the group becomes the group' s APP. D.S. Nagin [?] noted that when each group' s APP exceeds 70%, it indicates good grouping of all data in that group. It should be noted that during fitting, the above steps can be performed alternately, with adjustments made to previous steps based on actual results.

2.2 Measuring Paper Interdisciplinarity

To study the relationship between paper interdisciplinarity and citation trajectories, this study measures the interdisciplinary degree of papers and examines whether it influences citation patterns.

From the perspective of individual papers, we measure interdisciplinarity from two angles. Drawing on "forward"and "backward"citation relationships in patent citation analysis and A.L. Porter' s proposed integration and diffusion index models [?], we treat a paper' s "forward" citation relationship (citing documents) as a knowledge diffusion process, measuring diffusion degree across disciplines using a "disciplinary diffusion index." The "backward" citation relationship (references) is treated as a knowledge integration process, measured using a "disciplinary integration index."

Interdisciplinarity, or disciplinary diversity, is measured using A. Stirling' s diversity measurement model [?]. In this model, diversity quantification should comprehensively examine three basic characteristics: variety (the number of categories to which elements in the system belong), balance (the evenness of element distribution across categories), and disparity (differences between categories). The diversity formula combining these three elements is:

$$D = \sum d_{ij} \cdot p_i \cdot p_j$$

where p_i and p_j are the proportions of i and j in the system (balance), and d_{ij} is the difference degree between i and j (disparity), with summation reflecting system variety.

Based on this model, we measure two interdisciplinarity indicators: (1) **Integration Index (INT)**: Treating a paper' s reference set as a system, we calculate its interdisciplinarity. Using co-occurrence frequencies between different disciplines as the distance d_{ij} (disciplinary disparity characteristics) and the proportion of a discipline in all disciplines of the reference set as the balance characteristic, we calculate disciplinary diversity of the reference set using formula (1). (2) **Diffusivity Index (DIF)**: Treating a paper' s citing document set as a system, we calculate its interdisciplinarity. The calculation method for DIF is the same as for INT.

2.3 Data Sources

Data were obtained from the Web of Science database. Using Web of Science subject classifications, we selected "Library and Information Science" as the research field. A 10-year window was used as the citation trajectory development timeframe to examine citation patterns and changes after paper publication. We retrieved literature from 2003-2007 under the "Library and Information Science" classification. To exclude differences in citation patterns among document types (such as reviews, reports, and literature), we limited document type to "article," obtaining 10,406 records. After removing 1,884 zero-citation documents, 8,522 data records remained.

These literature citations showed excessive dispersion and uneven distribution, with over 60% having annual citation frequencies less than 1. When analyzing individual papers, excessive citation trend gaps between papers weaken trajectory characteristics during fitting, masking valuable information, reducing statistical analysis accuracy, and creating difficulties for curve fitting. For more granular analysis of citation trajectory curves and to reduce the impact of data dispersion, we hierarchically divided literature according to the Pareto principle: low-cited literature (annual citation frequency ≤ 1) with 5,258 papers, medium-cited literature ($1 <$ annual frequency ≤ 12) with 3,123 papers, and highly cited literature (annual frequency > 12) with 141 papers. Low-cited literature with annual citation frequency less than 1 shows minimal trend variation and thus was excluded from this study. We separately analyzed 3,123 medium-cited and 141 highly cited papers.

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3 Literature Citation Trajectory Analysis Based on Group-Based Models

3.1 Citation Trajectory Analysis of Highly Cited Literature

First, we determined the group range as 3-8 groups, using cubic polynomial equations to fit citation curves of 141 highly cited papers. We found that 4/5/7/8 group models failed to converge. Attempting to increase the regression equation power to quartic, we found the 8-group model still could not be fitted. When increasing to quintic power, all groups successfully converged. The BIC values for 3-8 group models were -5555.32, -5488.55, -5421.36, -5379.38, -5326.73, and -5300.14 respectively, indicating improved model fit. The curve fitting results are shown in Figure 1 [Figure 1: see original paper].

From the fitting results, as group numbers increase, trend curves become increasingly refined, with more curve types emerging. Meanwhile, BIC values increase, indicating better equation fit. However, comparing fitted graphs reveals that when preset group numbers exceed the optimal number, new categories contain less characteristic information, weakening group differentiation. When groups increased to 7, the refinement only occurred among low-cited literature: from 6 groups to 7 groups, three curves in Figure 1(d) (Group 2 (24.1%), Group 3 (63.4%), Group 4 (7.3%)) became four curves in Figure 1(e) (Group 2 (34%), Group 3 (49.2%), Group 4 (8.7%), Group 5 (2.9%)). Overall trends showed no new curve shapes. Therefore, we selected the more representative and concise 6-group fitting results (Figure 1(d)) for analysis.

Figure 1(d) shows that Groups 2 (24.1%) and 3 (63.4%) account for over 80% of literature, with very similar citation curve shapes—maintaining low and stable citation levels for a long time after publication. In Group 3 particularly, annual citation counts are less than 20 times. In contrast, Group 4 literature maintains relatively stable growth trends, with annual average citations at medium-low levels and sustained growth momentum over time, accounting for less than 10% of all highly cited literature and representing moderate influence.

Among the remaining three curves, Group 6 shows the highest overall citation level, maintaining stable growth throughout the 10-year period and representing literature with both high quality and high influence. Groups 1 and 5 have similar cumulative citation counts but completely different curve trends: Group 1 literature has low citations in the first 5 years after publication but maintains slow growth, with annual citations exceeding 100 times after the 7th year; Group 5 literature experiences rapid citation growth after publication, peaking in years 3-4, followed by gradual decline. This pattern appears in only 0.7% (1 paper) of literature, representing a small proportion of "temporary" citation types among highly cited papers. In 1985, E.S. Aversa identified two citation trends through literature clustering: "delayed growth-slow decline" and "immediate growth-rapid decline" [?]. S.E. Baumgartner and L. Leydesdorff similarly found these two patterns in six journals [?]. Compared with the "temporary" citation of Group 5, the peak of "persistent" citation curves like Group 1 generally appears later, with time differences between peaks varying by discipline and document type. Therefore, accurately measuring literature quality or influence within short time windows is difficult.

3.2 Citation Trajectory Analysis of Medium-Cited Literature

Similar to the highly cited literature analysis, we used quintic equations to fit 3,123 medium-cited papers. Comparing different group numbers revealed that BIC values gradually increased with more refined groups. Again, we focused more on higher-cited literature during model fitting, gradually increasing group numbers until no further refinement occurred among relatively highly cited groups. Figure 2 shows fitting results for 3-6 groups. Compared with the 4-group model (Figure 2(b)), the 5-group model produced new representative curves, while the 6-group model (Figure 2(d)) only refined low-cited literature without new trends compared to the 5-group model (Figure 2(c)). Therefore, we selected the 5-group model (Figure 2(c)) for analysis.

Figure 2(b) shows that in Groups 1 and 2, over 60% of literature has annual citation frequency ≤ 2 times within 10 years after publication. These two groups account for over 80% of total literature, similar to highly cited literature results. We also identified "persistent" citations (Groups 4 and 5) and "temporary" citations (Group 3) in medium-cited literature. Group 3 literature reaches citation peaks in years 2-3 after publication, often representing research on hot topics that initially attract widespread attention but decline as new theories or topics emerge. Group 4 citation curves maintain stable upward trends. Group 5 literature maintains continuously rising citation frequency after publication, representing the highest influence category.

As groups increased to 8, more combinations of "persistent" and "temporary" citations emerged. Figure 3(a) shows 8-group results, where higher-cited Groups 7 (0.6%) and 8 (2.2%), and lower-cited Groups 6 (3.8%) and 4 (7.4%) all show "temporary" and "persistent" characteristics. Similar to "temporary" literature in Figure 2(b), Groups 6 and 7 reach citation peaks in year 3 after publication, followed by declining citation frequency. When groups increased to 9 (Figure 3(b)), a new citation trajectory emerged: Group 9 literature (0.1%) in Figure 3(b) shows classic citation curve characteristics for the first 8 years, but with rapid citation growth at the lifecycle' s end, beginning a second life cycle. As it enters a second decline phase, its trend would develop into the "bimodal curve" described in literature [?].

4 The Influence of Interdisciplinary Characteristics on Citation Trajectories

Citation trajectory analysis not only distinguishes overall citation levels but also identifies literature influence persistence. Based on citation trajectory grouping results, we used the Multinomial Logit (MNL) model proposed by economist D. McFadden [?] to explore relationships between literature characteristics and citation patterns. The MNL model uses maximum likelihood estimation to assess how "category characteristics" or "individual traits" affect category selection. With solid theory and simple calculation, it is a classic model for analyzing influencing factors of multi-category dependent variables. We used this model to study the probability of papers appearing in each literature group and the relationship between citation patterns and interdisciplinarity.

As described above, using individual paper grouping results as dependent variables and paper interdisciplinarity as independent variables, we measured two indicators: Disciplinary Integration Index (INT) and Disciplinary Diffusivity Index (DIF). Control variables included number of authors (AUN), number of references (REN), paper length (PG), journal impact factor (IF), international collaboration (CON), and title length (TIL).

4.1 Interdisciplinary Influence on Highly Cited Literature

In the 6-group classification results for highly cited literature (Figure 1(d)), Group 5 is the only "temporary" citation group. Correspondingly, Groups 1, 4, and 6 can be considered "persistent" citations besides the clearly persistent Group 1. Table 1 shows that DIF and INT have significant relationships with citation trajectories. DIF is positively proportional to long-term citation probability—the broader the disciplinary diffusion, the more persistent the paper' s influence. This suggests exposure across wider disciplinary ranges helps papers maintain sustained attention, while narrow disciplinary scope makes influence more likely to fade over time. Such papers may propose universal methods or conclusions applicable across multiple fields, making them more likely to become enduring scientific contributions. Conversely, INT is inversely proportional to influence persistence—the greater the interdisciplinary degree of references and the higher the integration index, the higher the probability of "temporary" citation. Research absorbing multidisciplinary knowledge and highly interdisciplinary papers may have research depth limited by increased knowledge span, making such achievements' citation probability lower than more in-depth research in the same field.

Further analysis using Group 5 as the reference for multinomial fitting shows that in Group 5 indicators, both DIF (β = -15.92, p = 0.000) and INT (β = 254.47, p = 0.000) are significant, with DIF positively correlated with influence persistence and INT negatively correlated—consistent with previous conclusions. In Groups 1-4 indicators, both DIF and INT are non-significant, indicating that overall citation levels are not affected by disciplinary diversity.

4.2 Interdisciplinary Influence on Medium-Cited Literature

For medium-cited literature, using the 5-group results with Group 3 as the reference for model fitting, Table 2 shows that in distinguishing "persistent" citations (Groups 4 and 5 corresponding to Group 3' s "temporary" citations), DIF and INT show no significant influence. However, DIF (β = -0.43, p = 0.010; β = -0.34; p = 0.041) shows significant negative effects in Groups 1 and 2 results, indicating that smaller disciplinary diffusion indices make papers more likely to fall into low-citation groups (Groups 1 and 2). This suggests broader disciplinary diffusion increases overall citation levels, though the index doesn' t significantly distinguish between groups with similar overall levels (Groups 4 and 5), indicating limited scope and magnitude of effect.

Table 3 summarizes the influence of all indicators on citation trajectories for highly and medium-cited literature. Impact factor, as a traditional static cumulative citation metric, promotes sustained citations but only shows promotional effects on overall citation levels for medium-cited literature, not for highly cited literature. Reference count reflects knowledge absorption breadth to some extent. For medium-cited literature, reference count positively affects both overall citation level and influence persistence, but shows no clear relationship for highly cited literature. Paper length positively influences influence persistence for medium-cited literature.

Interdisciplinarity differentially affects highly and medium-cited literature. For highly cited papers, broader disciplinary diffusion means more persistent influence, while papers integrating more disciplinary knowledge tend to gain short-term attention. For medium-cited papers, broader disciplinary diffusion increases cumulative citation levels, but interdisciplinarity shows no clear relationship with sustained citation.

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5 Discussion and Conclusions

5.1 Research Conclusions

This study used group-based trajectory modeling to group literature by citation trends, revealing different citation patterns within ten years after publication, and explored the relationship between interdisciplinarity and citation trajectories. Conclusions are as follows:

(1) According to previous research, citation trajectories after publication mostly follow a rise-then-decline trend, fitting cubic polynomial shapes. Therefore, we initially used cubic polynomials to characterize citation curves, but multiple groups failed to converge. Quintic polynomials achieved good fitting results across all citation levels, indicating that in practice, whether for highly or medium-cited literature, citation curves may have multiple inflection points over longer time windows, making citation pattern dynamics a complex process.

(2) Two citation patterns were identified from citation curves: "persistent" and "temporary." The former shows a small rate of decline after reaching citation peaks, demonstrating sustained influence and still receiving high citations after ten years. The latter experiences rapid attention growth initially, peaking in years 2-4 after publication, followed by obvious decline, showing short-term high influence—mostly frontier or hot-topic articles. Subgroup analysis of highly and medium-cited literature shows that "persistent" and "temporary" phenomena exist across all citation levels, representing a universal phenomenon. Therefore, literature influence evaluation should consider citation patterns over longer time periods. "Temporary" citations mostly occur because research topics are hot at the time; as topic popularity fades, citation counts decline. More specific reasons and the dynamic mechanisms of citation system changes require further investigation combining paper content and research trends.

(3) Author count does not affect overall citation levels or influence persistence. Impact factor positively affects overall citation levels and influence persistence for medium-cited literature and influence persistence for highly cited literature, but shows no effect on overall citation levels for highly cited literature. Reference count reflects knowledge absorption breadth and positively affects both overall citation level and influence persistence for medium-cited literature, but shows no clear relationship for highly cited literature. Paper length positively promotes influence persistence for medium-cited literature.

(4) Interdisciplinarity somewhat influences citation trajectories. The relationship between interdisciplinarity and cumulative citation levels only appears in medium-cited literature. In distinguishing "persistent" from "temporary" citations, interdisciplinarity only affects highly cited literature—among papers with annual citations >12, broader disciplinary diffusion leads to more sustained citations, while papers integrating more disciplinary knowledge tend to gain short-term attention with subsequent citation declines.

5.2 Research Limitations

This study applied group-based trajectory modeling to analyze citation trajectories, fitting and grouping them to understand citation behavior beyond cumulative frequencies. However, this method has limitations. Judgments about group numbers and fitting equations for each subgroup still require subjective experience and optimal model selection based on results. Additionally, when systems are complex, data volumes large, outliers exist, or models are complex, fitting may not converge. Therefore, GBTM only provides a method for studying citation trajectories over longer time periods under certain conditions.

Second, although we fitted citation trajectories within a certain range, individual paper trajectory characteristics were ignored. During literature citation lifecycles, multiple citation peaks may occur. However, since fitting and grouping mainly extract common features, individual characteristics are weakened and cannot be fully reflected. Nevertheless, citation trajectory grouping provides possibilities for more granular citation pattern research—by observing different trajectory types, we can conduct deeper mining of literature characteristics for specific groups.

Moreover, citation trajectories only reflect direct citation counts, considering only direct influence, while literature impact is not always direct. X. Hu et al. [**?**] noted that direct citation counts sometimes cannot reflect true paper influence, as some literature' s impact manifests through "trigger effects" that cause other papers to be cited. Therefore, comprehensively evaluating literature influence still requires incorporating indirect citations and citation cascade structures.

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Author Contributions: Shi Yanqing: Responsible for research framework design and paper writing; Zhao Yifang: Responsible for data processing and debugging.

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