An Evaluation Method for the Innovativeness of Individual Academic Papers Based on Research Topic Comparison (Postprint)

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Abstract

[Purpose/Significance] Innovation represents a fundamental requirement of academic papers, and the effective evaluation of paper innovativeness has consistently attracted considerable attention from experts and scholars globally. With the development of information technology, employing computational techniques to evaluate the innovativeness of individual academic papers from a content perspective has gradually become viable. [Method/Process] This paper proposes an evaluation method for the innovativeness of individual academic papers based on research topic comparison. The method initially employs the Keygraph algorithm to extract keywords representing the paper's research topics, subsequently calculates the similarity between the paper's research topics and frontier topics in scientific research, and ultimately develops a comprehensive evaluation model for paper innovativeness by integrating two external indicators: journal impact factor and Altmetrics. [Results/Conclusion] Empirical validation within the research domain of "carbon nanotube" materials demonstrates that the proposed method can effectively, rapidly, and accurately evaluate the innovativeness of individual academic papers from a content perspective.

Full Text

A Method for Evaluating the Innovation of Single Academic Papers Based on Research Theme Comparison

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Abstract

[**Purpose/Significance**] Innovation is the essential requirement of academic papers, and how to effectively evaluate the innovation of academic papers has long been a concern for experts and scholars worldwide. With the development of information technology, it has gradually become possible to use computer technology to evaluate the innovation of single academic papers from the perspective of paper content.

[**Method/Process**] This paper proposes a method to evaluate the innovation of single academic papers based on research theme comparison. The method first uses the Keygraph algorithm to extract keywords representing the paper's research theme, then calculates the similarity between the paper's research theme and the scientific research frontier theme, and finally proposes a comprehensive evaluation model for paper innovation by combining two external indicators: journal impact factor and Altmetrics.

[**Result/Conclusion**] An empirical study in the field of carbon nanotube materials research demonstrates that this method can effectively, quickly, and accurately evaluate the innovation of single academic papers from the perspective of paper content.

Keywords: Academic Papers; Innovation; Research Theme; Journal Prestige; Altmetrics
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Academic papers, as one of the main forms of scientific research output, have long been a hot spot and focus in bibliometrics research regarding their innovation evaluation methods. Through the evaluation of academic paper innovation, we can foresee scientific events that will have a major impact on the future scientific community, thereby prompting relevant scientific research management institutions to formulate effective science and technology policies and helping research institutions and scholars engage in more relevant frontier research, thus effectively promoting the development of science and technology.

Due to the complexity and diversity of innovation itself, there is currently no universally recognized indicator or method for evaluating academic paper innovation. Through reviewing relevant research, we find that the most internationally recognized method is peer review. Peer review is a subjective qualitative evaluation method. While it plays an important role in paper innovation evaluation, it also reveals some problems, such as the non-impartiality, non-objectivity, and non-rationality of evaluation results caused by the characteristics of individual review experts' cognition.

Citation analysis is currently the most mainstream method for evaluating paper influence. Scholars generally believe that the higher the citation count of a paper, the greater its influence. In the field of bibliometrics, some scholars have also explored the quantitative evaluation of paper innovation through citation counts. In 2013, B. Uzzi et al. published a paper in *Science* arguing that papers with high innovation characteristics are more likely to become highly cited papers. Research by Shen Lü and Ren Haiying et al. also proves that there is a certain positive correlation between paper innovation and citation count. However, as is well known, citation indicators have obvious time lag problems, meaning they cannot evaluate paper innovation immediately upon publication but require historical data accumulation.

Due to the limitations of citation-based academic paper innovation evaluation, researchers have begun to focus on the content of academic papers themselves, constructing measurement indicators for academic paper innovation through content analysis and mining. For example, Shen Yang, D. Yogatama et al., and Yang Jianlin et al. used paper titles and keywords to evaluate paper innovation. Zhu Daming et al. evaluated paper innovation from the perspective of references. Suo Chuanjun et al. used the number of knowledge unit transfers in academic papers to measure the aging and innovation degree of single academic papers. Although paper titles, keywords, references, etc., can to some extent reflect important themes, ideas, concepts, or methods contained in academic papers, these indicators have loose relationships or do not directly combine with the conceptual and semantic attributes of potentially innovative topics, and cannot fully reflect the innovation value of papers. With the development of information technology, using natural language processing technology to evaluate paper innovation from the perspective of paper content has gradually become possible. This paper argues that if a paper's research theme aligns with current scientific research frontier themes and is published in a journal with a high impact factor, then the paper has high innovation. Based on this, we propose a method to evaluate the innovation of single academic papers based on research theme comparison, which comprehensively evaluates single academic papers by combining research theme, Altmetrics indicators, and journal impact factor to construct a comprehensive evaluation system for single academic paper innovation.

2 Related Research

2.1 Concept Definition

Academic paper influence and innovation are two easily confused concepts. Academic paper influence mainly includes two aspects: academic influence and social influence. Academic influence refers to the positive or negative research evaluation that academic papers generate in the academic community or their discipline and adjacent disciplines, mainly achieved through peer review and paper citations; social influence mainly refers to the positive and negative evaluation generated by a paper at the social level outside academia, mainly reflected in the degree of attention from social audiences, and is a feedback evaluation from publishing institutions and social audiences.

Academic paper innovation has certain complexity and diversity, and scholars have expressed their own definitions and standards for the connotation and criteria of academic paper innovation from different perspectives. Chen Jianqing defines academic paper "innovation" as establishing or developing valuable new theories, new specialties, new methods, new technologies, etc. in relevant academic fields, or processing, sorting, refining, and excavating new ideas based on previous research results and experience, and proposing new conclusions different from existing conclusions in the participated demonstration topics. Zhou Luyang combs the indicator system of academic paper innovation factors, believing that paper innovation factors mainly lie in new arguments and new evidence. New arguments include new theories, new methods, new countermeasures, and new disciplines; new evidence includes new data and new facts, where new data refers to first-hand data obtained through surveys or experiments, and new facts refer to phenomena revealed for the first time. T. Heinze et al. summarize highly innovative research as: revolutionary new theories, discovering new phenomena, proposing and using new methods, inventing new instruments, and integrating existing theories from new perspectives. Ye Liang et al. believe that innovation includes two characteristics: usefulness and novelty, where usefulness emphasizes appropriateness, effectiveness, and value, and novelty emphasizes uniqueness and rarity. Yang Jianlin et al. believe that topic novelty is one of the most essential features of academic paper innovation, including new concepts, new ideas, and new models.

In summary, this paper evaluates paper innovation through paper research themes, defining and quantifying topic novelty as the primary task of paper innovation evaluation. Evaluating papers through research themes is innovation evaluation at the "new argument" level.

2.2 Paper Topic Automatic Identification Research

Automatic identification of academic paper topics has always been a research hotspot in data mining and information recommendation. Many scholars have used different technologies and methods to conduct automatic identification research on paper topics to help researchers quickly grasp paper themes and improve research efficiency. Guo Hongmei et al. summarized the main paper topic identification methods at home and abroad into the following five categories:

(1) Frequency statistical methods. This method mainly identifies topics through word frequency statistics and word distribution in papers. Current research on this method is relatively mature. Its advantage is simplicity, but its disadvantage is that it considers word features in isolation and ignores the mutual influence of words in the text, and cannot reveal low-frequency words representing paper themes.

(2) External dictionary methods. Representative methods include those based on WordNet and MESH dictionaries. Although external dictionary methods can well reflect the mapping relationship of concepts in dictionaries, they are divorced from text content, and unrecorded words lead to missing new words, making it impossible to fully reveal paper themes.

(3) Latent semantic indexing methods. The LDA method based on latent semantic indexing identifies topics according to the probability of words appearing in documents, which can expand the semantic coverage of identified topics. The disadvantage is that it is prone to noise and requires manually specifying clustering coefficients, which are empirical values difficult to obtain.

(4) Centrality methods. This method analyzes text from a network perspective, with representative indicators including betweenness centrality, degree centrality, and closeness centrality. Centrality methods comprehensively consider multiple grammatical and semantic relationships between words, but many algorithms can only be applied to small-scale undirected graphs and are difficult to implement for large-scale complex networks.

(5) Subgraph mining methods. This method mainly identifies core terms or associated subgroups in graphs based on the attributes of edges or nodes to reveal the main content of papers. Subgraph mining is a new paper topic identification method that needs in-depth exploration, and research on this method is not yet mature and needs further deepening.

In summary, frequency statistical methods are relatively mature and can effectively identify paper research topics. M. Yang et al.'s experimental results show that among frequency statistical methods, the Keygraph algorithm can effectively overcome the problem of failing to extract low-frequency words representing paper themes. If Keygraph extracts few keywords, most keywords carry important ideas, and Keygraph can play a good role in helping users find documents matching their ideas or special interests. Therefore, this paper selects the Keygraph algorithm to extract paper research themes.

2.3 Keygraph Algorithm

The Keygraph algorithm was proposed by Professor Y. Ohsawa of Tokyo University in 1998. This algorithm can extract keywords representing the main ideas of documents without relying on additional tools (such as document collections or natural language processing tools). The algorithm is based on the idea of graph segmentation, treating documents as graphs where co-occurring words in documents are placed in clusters, with each cluster mapping the author's main viewpoints. The relationships between words in clusters are statistically analyzed, and top-ranked words are selected as the document's keywords. The ultimate goal of Keygraph is to index main keywords reflecting the author's viewpoints rather than words with high frequency.

The words carried by document D are related to the author's expressed viewpoints. Document D is likened to a constructed building with foundation, walls, doors, and windows, as shown in Figure 1 [Figure 1: see original paper]. The roof represents the document's main viewpoint, supported by columns, and each building needs a roof. Term clusters constitute other parts of the building. Assuming document D consists of sentences, and each sentence consists of words, the Keygraph algorithm extracts keywords through the following steps:

(1) Document preparation. Preprocess the document, including removing stop words, converting synonyms, and restoring word roots. Then automatically segment the document and extract high-frequency words above a threshold, building a word list sorted by frequency.

(2) Extract high-frequency links. Links represent word pairs that frequently appear in the same sentence. This step mainly counts word pairs co-occurring within the same sentence in the document, sorts them, and extracts high-frequency co-occurring word pairs above a specified threshold as high-frequency links.

(3) Extract important words and important links. Important words refer to words connecting high-frequency word groups. This step calculates the frequency of co-occurrence between all words in the document and a group of high-frequency words, extracts those with co-occurrence frequency above a specified threshold as important words, and for each high-frequency word and each important word, calculates their co-occurrence frequency in the same sentence and sorts them. When the co-occurrence frequency is above a specified threshold, the link is considered an important link.

(4) Extract keywords. This involves extracting keywords representing the document's main viewpoints. Each important word is sorted according to the sum of co-occurrence values of its connected important links. When above a specified threshold, the represented term is extracted as a keyword.

3 Research Approach

The specific research approach for evaluating single academic paper innovation based on research theme comparison is as follows: Obtain papers in the same discipline to construct an experimental dataset; Conduct data preprocessing, including segmentation and stop word removal; Use the Keygraph algorithm to extract keywords representing paper research themes; Obtain scientific research frontier themes in the discipline; Calculate similarity between paper research themes and scientific research frontier themes; Combine journal prestige and altmetrics indicators to comprehensively determine paper innovation. As shown in Figure 2 [Figure 2: see original paper]:

3.1 Theme Similarity Calculation

After using Keygraph to extract keywords representing paper research themes, we need to obtain scientific research frontier themes in the discipline and then calculate similarity between paper themes and scientific research frontier themes. Common similarity calculation methods include word overlap calculation, geometric distance-based calculation, and word difference set calculation. Since Keygraph extracts theme words representing paper research themes, this paper uses the Jaccard coefficient for word overlap calculation to determine similarity. The Jaccard coefficient is an indicator used to quantify the similarity between two sets. This method treats sentences as word sets; the more theme words they share, the greater their similarity. For any two sets A and B containing the same type of elements, with C(A) representing the number of paper theme words and C(B) representing the number of scientific research frontier theme words, their Jaccard coefficient is shown in Formula (1):

$$Jaccard\ Coefficient = \frac{C(A \cap B)}{C(A \cup B)}$$

Formula (1)

The Jaccard coefficient calculates the similarity between each paper and the scientific research frontier, denoted as Simi.

3.2 Comprehensive Evaluation of Academic Paper Innovation Based on Theme Comparison

Through the above steps, we can filter papers that match scientific research frontier themes. However, not all papers matching scientific research frontier themes have high innovation, as many papers may follow hot topics without necessarily containing innovative concepts or ideas. Therefore, this paper combines external indicators for comprehensive evaluation. Journal impact factor and Altmetrics are the two most commonly used methods for evaluating paper influence, and their values can be obtained immediately upon paper publication without time lag. Altmetrics focuses on the dissemination and discussion degree of academic papers on social networks, public opinion media, and online academic tools. The fast and wide-ranging characteristics of network dissemination avoid the low speed and long cycle problems of citation analysis. Wang Xianwen et al. point out that when a paper has good novelty and topicality, it can be more widely disseminated on social networks. Therefore, Altmetrics can help identify papers with high innovation. Journal impact factor has long been considered an effective way to evaluate papers, and Yang Jianlin's empirical research proves that within the same discipline, papers published in important core journals have higher average topic novelty. Therefore, this paper combines Altmetrics and journal impact factor for comprehensive evaluation. Altmetrics data is obtained through Altmetrics Explorer, which can evaluate papers according to various indicators including Blog, News Outlets, Twitter, Weibo, Facebook, and Wikipedia, providing the paper's AltmetricScore, which is used as the altmetrics indicator value, denoted as Alti. Journal impact factor is denoted as IFi.

In comprehensive evaluation strategies, since the importance and status of each sub-indicator differ, different weights should be determined for each sub-indicator to ensure scientific evaluation. Currently, common comprehensive evaluation strategies include the Analytic Hierarchy Process, linear weighted summation method, fuzzy comprehensive evaluation method, and TOPSIS method. Given the large numerical differences among Simi, IFi, and Alti indicators, this paper selects the TOPSIS method as the final comprehensive evaluation strategy. TOPSIS is typically used for comprehensive analysis and evaluation of objects with multiple indicators. It can fully utilize original data information to normalize evaluation indicators, assign reasonable weights to each indicator, and conduct objective evaluation of each object, overcoming the defect of subjective weighting. The basic principle of TOPSIS is to construct a normalized original data space matrix for evaluation indicators. Papers to be evaluated can be regarded as points in space. For each paper's three indicators (Simi, IFi, Alti), select the optimal value (maximum value in evaluation indicators) and the worst value (minimum value in evaluation indicators) from all points, then calculate the distance from each point to the optimal and worst values, denoted as Di_{max} and Di_{min} respectively, to obtain the relative closeness Si of the paper to be evaluated to the optimal and worst values. Papers are comprehensively evaluated according to Si values. Specific calculation steps are shown in Formulas (2), (3), and (4):

$$D_i^{max} = \sqrt{(Sim_i - Sim_{max})^2 + (IF_i - IF_{max})^2 + (Alt_i - Alt_{max})^2}$$

Formula (2)

$$D_i^{min} = \sqrt{(Sim_i - Sim_{min})^2 + (IF_i - IF_{min})^2 + (Alt_i - Alt_{min})^2}$$

Formula (3)

$$S_i = \frac{D_i^{min}}{D_i^{min} + D_i^{max}}$$

Formula (4)

Where Sim_{max} represents the optimal value in the paper similarity evaluation indicator; IF_{max} represents the optimal value in the journal impact factor evaluation indicator; Alt_{max} represents the optimal value in the altmetrics evaluation indicator; Sim_{min} represents the worst value in the paper similarity evaluation indicator; IF_{min} represents the worst value in the journal impact factor evaluation indicator; Alt_{min} represents the worst value in the altmetrics evaluation indicator; Di_{max} represents the distance from the evaluated paper's 0-1 converted value of each rating indicator to the optimal value of that indicator; Di_{min} represents the distance from the evaluated paper's 0-1 converted value of each rating indicator to the worst value of that indicator; Si represents the final comprehensive evaluation value of the paper.

Finally, papers are comprehensively sorted according to Si values, with papers having excellent S values considered to have high innovation (the smaller the S value, the more excellent).

4 Empirical Study

This paper selects the carbon nanotube materials research field to verify the proposed method for evaluating single academic paper innovation based on research theme comparison. The specific process is as follows:

4.1 Construct Search Strategy and Obtain Experimental Dataset

Based on expert consultation, this paper constructs the following search strategy for the carbon nanotube materials research field: (TI=("carbon nanotube*") OR TI=("carbon?nanotube*") OR TI=("CNT*") OR TI=("DWNT*") OR TI=("MWNT*") OR TI=("SWNT*") OR TI=("MWCNT*") OR TI=("SWCNT*") OR TI=("DWCNT*")) AND (TI=(yarn*) OR TI=(fibre*) OR TI=(fiber*) OR TI=(sheet*) OR TI=(forest*) OR TI=(spun*) OR TI=(spin*)), selecting the SSCI, SCI-EXPANDED, and CPCI-S databases with a time span of 2010-2013, retrieving a total of 1,232 documents (search date: April 15, 2017).

Regarding the time span, since Altmetrics emerged in 2010 and papers after 2010 can obtain their AltmetricScore, this paper selects 2010 as the starting search time. Subsequent research will correlate paper S values with citation counts to verify the effectiveness of the proposed method. Through observation, it was found that papers in the carbon nanotube materials field after 2013 have low citation counts and insufficient citation accumulation, so 2013 is selected as the end search time for empirical analysis of papers from 2010-2013.

The distribution of literature in the carbon nanotube materials research field from 2010-2013 is shown in Figure 3 [Figure 3: see original paper]. As can be seen from Figure 3, the annual publication numbers from 2010-2013 are not significantly different. There was a slight increase from 2010-2011, a more obvious upward trend from 2011-2012, and a slight decrease from 2012-2013.

Through preliminary analysis of search results, this paper selects 408 papers published by the top 10 institutions by publication volume (see Table 1) for subsequent full-text analysis.

4.2 Data Preprocessing

The main tasks in the data preprocessing stage include format conversion, segmentation, stop word removal, and case conversion for the obtained 408 papers.
Format conversion: Convert 408 PDF papers to plain text format; Segmentation: Split each paper into word-level units; Stop word processing: Stop words mainly include numbers, mathematical characters, English symbols, punctuation marks, etc., such as "a, the, or, in". Stop words appear frequently in papers but have no actual meaning. Removing these stop words can reduce computational load and make the extracted keywords representing paper research themes more concise and accurate. All the above work is completed using KNIME software from German company KNIME.

4.3 Keygraph Algorithm Extraction of Keywords Representing Paper Research Themes

The main task at this stage is to extract keywords from each paper using Keygraph. The accuracy of keyword extraction directly affects the experimental results. This is implemented through the Keygraph keyword extractor module in KNIME, with specific experimental module configuration shown in Figure 4 [Figure 4: see original paper]. To maximize the revelation of paper research themes, this paper sets the number of keywords extracted from each paper to 10, obtaining 4,080 keywords representing paper research themes from 408 papers. Partial extraction results are shown in Figure 5 [Figure 5: see original paper].

As can be seen from Figure 5, keyword extraction for the paper titled "Continuous multi-layered carbon nanotube yarns" yields 10 keywords representing the paper's research theme. The Score in the figure represents the contribution value calculated according to the Keygraph algorithm for each keyword's role in expressing the paper's research theme.

4.4 Theme Similarity Calculation Based on Jaccard Coefficient

For the scientific research frontier themes in the carbon nanotube materials research field from 2010-2013, this paper uses CiteSpace developed by Dr. Chen Chaomei to reveal them. CiteSpace analyzes data downloaded from Web of Science, with partial frontier theme evolution trends shown in Figure 6 [Figure 6: see original paper]. Through analysis of clustering results, 20 research frontier themes are selected. The annual research frontier theme words in the carbon nanotube materials research field from 2010-2013 are shown in Table 2 .

After extracting the stems of the above scientific research frontier theme words, R language is used for Jaccard similarity calculation to obtain Sim values for each paper. Through analysis of calculation results, this paper sets the threshold at 0.3, obtaining 96 eligible papers. The top three papers by Sim value for each year from 2010-2013 are shown in Table 3 .

As shown in Table 3, for 2010 papers, the paper titled "Carbon nanotube grafted carbon fibres: a study of wetting and fibre fragmentation" has the highest Sim value of 0.82. The maximum Sim values for 2011, 2012, and 2013 are 0.78, 0.73, and 0.79 respectively.

4.5 Comprehensive Evaluation of Academic Paper Innovation Based on TOPSIS

Obtain the journal impact factor indicator value (IFi) for each paper through the Chinese Academy of Sciences JCR partition data, then obtain the altmetrics indicator value (Alti) through Altmetrics Explorer, and finally calculate the S value for each paper using the TOPSIS method. This paper first uses Histcite software to screen highly cited papers from 1,232 papers, as shown in Figure 7 [Figure 7: see original paper] (in the figure, numbers inside circles represent highly cited papers for that year, larger circles indicate higher citation counts, and lines indicate citation relationships between papers).

As can be seen from Figure 7, the citation relationships among papers in the carbon nanotube materials field from 2010-2013 are as follows: (1) For 2010 papers, paper No. 49 received the highest citation count of 125, titled “Continuous multi-layered carbon nanotube yarns,” published in *Advanced Materials*; papers No. 144, 138, and 63 also received relatively high citation counts of 116, 91, and 88 respectively. (2) For 2011 papers, paper No. 254 received the highest citation count of 180, titled “Superaligned carbon nanotube arrays, films, and yarns: a road to applications,” also published in *Advanced Materials*; papers No. 298, 352, and 264 also received relatively high citation counts of 89, 70, and 60 respectively. (3) For 2012 papers, paper No. 672 received the highest citation count of 143, titled “Electrically, chemically, and photonically powered torsional and tensile actuation of hybrid carbon nanotube yarn muscles,” published in *Science*; papers No. 515 and 622 also received relatively high citation counts of 93 and 63 respectively. (4) For 2013 papers, paper No. 744 received the highest citation count of 284, titled “Strong, light, multifunctional fibers of carbon nanotubes with ultrahigh conductivity,” published in *Science*; papers No. 767, 782, and 747 also received relatively high citation counts of 251, 216, and 63 respectively.

Next, this paper selects the top 3 papers by S value each year and conducts comparative analysis between S values and citation counts, with results shown in Table 4 .

This paper uses Pearson correlation coefficient to analyze the correlation between paper S values and citation counts. Pearson correlation coefficient is commonly used to measure the linear correlation between two random variables X and Y, with the calculation formula as follows:

$$r = \frac{N\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{[N\sum x_i^2 - (\sum x_i)^2][N\sum y_i^2 - (\sum y_i)^2]}}$$

Formula (5)

Substituting the data from Table 4 into Formula (5), the correlation coefficients between paper S values and citation counts for 2010, 2011, 2012, and 2013 are calculated as -0.32, -0.87, -0.98, and -0.74 respectively. These correlation coefficient values indicate a strong negative correlation between paper S values and citation counts, showing that the more excellent the S value (the smaller the value), the higher the paper’s citation count and the greater its innovation. The following is an analysis of S values and citation counts for papers each year: (1) For 2010 papers, paper No. 1 has the optimal S value and simultaneously receives the highest citation frequency of 125. Papers No. 2 and 3 have relatively optimal S values and belong to highly cited papers in the Histcite citation analysis graph, with citation frequencies of 91 and 116 respectively. (2) For 2011 papers, paper

No. 4 has the optimal S value and simultaneously receives the highest citation frequency of 180. Papers No. 5 and 6 have relatively optimal S values and also belong to highly cited papers in the Histcite citation analysis graph, with citation frequencies of 70 and 54 respectively. (3) For paper No. 7 in 2012 and paper No. 10 in 2013, both have optimal S values among papers in their respective years and simultaneously receive the highest citation counts. Papers No. 8, 9, 11, and 12 also have relatively optimal S values and all belong to highly cited papers in the Histcite citation analysis graph.

In summary, papers that match scientific research frontier themes and have high journal prestige and altmetrics indicators have optimal S values and simultaneously receive high citation counts. The above experimental results prove that the proposed method can relatively accurately evaluate the innovation of single academic papers from the perspective of paper content and effectively identify papers with high innovation.

Conclusion

Identifying academic papers with potential innovative topic concepts and semantic attributes is of great significance for scientific research. This paper proposes a method to evaluate the innovation of single academic papers based on research theme comparison. The method first extracts keywords representing paper research themes through the Keygraph algorithm, then calculates similarity between paper themes and scientific research frontier themes, and finally comprehensively evaluates paper innovation through the TOPSIS method by combining two external indicators: journal impact factor and Altmetrics. Through empirical research on papers in the carbon nanotube materials field, the study finds a strong correlation between paper S values and their citation counts; papers with more excellent S values have relatively higher citation counts. Experimental results show that the method can evaluate the innovation of single academic papers from the perspective of paper content relatively accurately.

The main contribution of this paper lies in attempting to use natural language processing technology to evaluate paper innovation from the perspective of paper research themes. Compared with traditional methods, this method has two advantages: (1) It overcomes the time lag problem of traditional citation analysis methods in evaluating paper innovation. Paper theme similarity values, journal impact factors, and Altmetrics indicators can all be obtained immediately upon paper publication. Therefore, compared with traditional citation analysis methods, this method does not require historical data accumulation and can quickly evaluate papers after publication, helping researchers timely identify papers with high innovation. (2) Citation analysis indicators, journal impact factors, Altmetrics indicators, etc., are all external indicators that have loose relationships or do not directly combine with paper innovation topic concepts and cannot fully reflect paper innovation value. With the development of information technology, especially natural language processing, full-text retrieval, and text mining technologies, evaluating paper innovation from internal paper perspectives has gradually become possible. This paper uses natural language processing technology from the paper research theme perspective, supplemented by two external indicators of journal impact factor and Altmetrics, for comprehensive evaluation, which better matches the concept of paper innovation themes.

However, this study still has certain limitations: The proposed method uses journal impact factor and Altmetrics indicator values as evaluation indicators, but these indicator values have certain instability, and their reliability is also questioned by many experts and scholars, which to some extent affects the evaluation results of this method; This paper uses scientific research frontier themes to evaluate academic paper innovation at the "new argument" level. Some review papers may have themes that match scientific research frontier themes and may be published in high-level journals, but their innovation is not high, and the proposed method cannot automatically exclude review papers.

In view of these limitations, future research will, on the one hand, improve paper theme word extraction algorithms and add more external indicators such as references and author prestige for more comprehensive and objective evaluation of paper innovation; on the other hand, conduct empirical research on papers in more fields to improve the robustness and generalization ability of the method.

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Author Contributions

Yang Jing: Responsible for data collection and paper writing;
Wang Fang: Reviewed paper structure and content;
Bai Rujiang: Proposed the research idea.

A Method to Evaluate Academic Papers' Innovation Based on the Research Theme Comparing

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Abstract: [Purpose/significance] Innovation is the essence requirement of academic papers, and how to effectively evaluate the innovation of academic papers has been concerned by experts and scholars at home and abroad. With the development of information technology, it becomes possible to use computer technology to evaluate the innovation of a single academic paper from the perspective of paper content. [Method/process] This paper presents a method to evaluate papers' innovation based on the research theme comparing. Firstly, Keygraph algorithm is used to extract keywords which represent papers' theme. Then, the similarity of the research theme and the scientific research front theme is calculated. Lastly, a comprehensive model is presented to determine the level of papers' innovation by two external indicators including the journal impact factor and altmetrics. [Result/conclusion] An empirical study of carbon nanotube field demonstrated that this method can evaluate papers' innovation from the perspective of paper content effectively, quickly and accurately.

Keywords: academic paper; innovation; research theme; journal reputation; altmetrics