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A new method for measuring the originality of academic articles based on knowledge units in semantic networks

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ABSTRACT

Research on the evaluation of the quality of academic papers is attracting more attention from scholars in scientometrics. However, most previous researches have assessed paper quality based on external indicators, such as citations, which failed to account for the content of the research. To that end, this paper proposed a new method for measuring a paper's originality. The method was based on knowledge units in semantic networks, focusing on the relationship and semantic similarity of different knowledge units. Connectivity and path similarity between different content elements were used in particular networks as indicators of originality. This study used papers published between 2014 and 2018 in three categories (i.e. Library & Information Science, Educational Psychology, and Carbon Nanotubes) and divided their content into three parts (i.e. research topics, research methods and research results). It was found that the originality in all categories increase each year. Furthermore, a comparison of our new method with previous models of citation network analysis and knowledge combination analysis showed that our new method is better than those previous methods when used in measuring originality.

1. Introduction

Academic papers are one of the most important outputs of scientific research. One of the core research topics in scientometrics is how to ensure objective, accurate, and fair evaluations of the quality of academic papers. Such evaluations would help to show the progress of scientific research and stimulate the enthusiasm and the creativity of scholars (Mingers & Leydesdorff, 2015). Traditionally, researchers considered the external indicators represented by citation as the important reflection of paper quality. Therefore, there were many previous researches measuring the quality of papers with citation analyses and other similar methods such as Altmetrics (Bornmann, 2014; Bornmann et al., 2019a; Konkiel & Scherer, 2013; Mingers & Leydesdorff, 2015; Roemer & Borchardt, 2012). However, most external indicators will be affected by lots of other non-academic factors such as the reputation of the authors/tweeters. A growing consensus has emerged among researchers that these external indicators are the impact of the paper, not its quality. As this consensus emerged, researchers began to measure paper quality based on their content and many content-related indicators occurred, which originality became popular as an important element of academic papers' quality (Bourke & Holbrook, 2013; Leydesdorff et al., 2016).

Although originality is one of the major quality guidelines and is extremely important in scientific research, measuring originality objectively with quantitative methods is difficult (Guetzkow et al., 2004; Shibayama & Wang, 2020). For this reason, a paper's originality is typically assessed by peer review (Feist, 2008). However, although peer review does provide a mechanism for measuring originality and is widely used, it also runs the risk of being subjective, preferential and conservative (Bornmann, 2011; Campanario, 1998;

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Irvine et al., 1985). The progress in bibliometric and computer-based analyses has led to considerable advancements in evaluating the quality of research papers (Azoulay et al., 2011; Boudreau et al., 2016; Fleming, 2001; Funk & Owen-Smith, 2017; Kogut & Zander, 1992; Nelson & Winter, 1982; Uzzi et al., 2013; Weitzman, 1996). Nevertheless, most of these methods only measured the originality of a paper by part of the content.

Our study aims to improve the currently used originality measuring methods by knowledge combination. The study proposed a new method for assessing the originality of a paper based on the semantic network of its content. Compared with previous methods, our method developed a new way of knowledge combination to assess the originality of a paper, considering the paper's content and structure (i.e. research topics, research methodology and results).

The proposed method offered a practical and theoretical scientometric means of evaluating the originality of academic papers. The results of this study demonstrated the effectiveness of our new method. In section two we discuss and compare different concepts of originality, with reference to the measurement of originality in previous studies. The research process and the data sources used in this study are described in the third section and the results of the analysis and explanations of the effectiveness of the proposed method through a comparison with other approaches are reported in section four. In the final section we discuss and conclude the results of this study as well as point out some limitations.

2. Literature review

In scientometrics, the development of methods for evaluating scientific originality can be divided into two stages. In the past, researchers made no clear distinction between the influence and the originality of a paper with the result that influence was typically used to measure the level of originality. Then the external indices (such as citations) were widely used to assess originality. However, more researchers have recently started analyzing the concept of originality deeply, and their studies were aided by the rapid development of semantic and network analyses. This has led to the creation of content-oriented and semantic-level methodologies, including text-based and keyword-based semantic network analyses. The following parts will review the concept of originality, and the existing methods used to evaluate it. It is vital to explore these aspects to understand what originality is, and how knowledge units in semantic networks can help to assess it.

2.1. Knowledge unit

A knowledge unit is the basic unit of knowledge control and processing and is the premise of all knowledge management activities (Wen, 2007). A knowledge unit has the following characteristics:

First, a knowledge unit represents complete knowledge. It is a complete semantic unit with complete semantic expression. Second, a knowledge unit is relatively independent in content and knowledge movement. Third, a knowledge unit is non-separable in semantic logic (Wang, 2003; Wen, 2007; Li et al., 2021). To sum up, the term knowledge unit used in the present study refers to the professional phrase that can represent a relatively complete knowledge, for instance, the phrase "Author Co-citation Analysis".

2.2. Originality and other similar concepts

Although originality plays an especially important role in scientific research, there is no clear consensus on its definition (Dirk, 1999; Guetzkow et al., 2004). Some literature in the sociology of science have argued that scisentific discoveries can either conform to tradition or depart from it, but only the latter is considered original (Bourdieu, 1975). Some researchers hold the view that originality exists in anything that adds something new to human knowledge, for instance, a newly asked scientific question, a newly proposed research method, newly obtained data and a newly developed theory (Dirk, 1999; Ziman, 2003). This view implies that originality can be methodological, theoretical, data-driven and results-based or even a mixture of them all (Shibayama & Wang, 2020). In the Research Excellence Framework (REF), originality refers to the extent to which a scientific output contributes to the knowledge in a given research field. The contribution includes discoveries, explanations, solutions to complex problems, proposals of original research methods, expansions of the horizons for research, proposals for new theoretical perspectives, collection of new data, etc. In general, originality can be measured by the extent to which a paper is original in terms of its research topics, methods, data, conclusion and other components. Other noteworthy is that originality is referred to as novelty in some papers (Shibayama & Wang, 2020; Uzzi et al., 2013; Yan et al. 2020).

The term originality frequently appears with the term creativity and innovation, with its definition still being controversial (Acar et al., 2017; Baruah et al., 2021; Colin, 2017; Joy, 2012; Ostermaier & Uhl, 2020). Many studies have considered originality a prerequisite for creativity and innovation (Hennessey & Beth, 1994; Mayer, 1999; Runco & Jaeger, 2012) and is correlated with both (Acar et al., 2017). In other words, while originality may not be exactly equivalent to either creativity or innovation, it is, at least, a major component of them. Recently, the concept of disruptiveness which is proposed by Funk and Owen-Smith (2017) and transferred to bibliometrics by Wu et al. (2019) has led to a widespread discussion. The Disruption Index Wu et al. (2019) was proposed to measure whether a paper destabilize or consolidate existing researches. It is suggested that disruptive papers "represent punctuated advances beyond previous theory, methods or findings" (Funk & Owen-Smith, 2017; Wu et al., 2019). Compared with originality, disruption refers to advances or interruption to previous knowledge, while originality emphasizes on novel knowledge that is significantly different from existing knowledge. To sum up, these concepts are closely related. Several studies have demonstrated the interrelationships between them (Bornmann & Tekles, 2021; Lin et al., 2022).

As described above, originality, which is associated with new knowledge creation, could provide alternative paths (including theory, method, algorithm and conclusion) for scientists to resolve scientific or technological issues. Thus, originality usually implies the progress of taking the first step into the unknown (from zero to one) and forming a new consolidation or bridge to intellectual space (Zeng et al., 2017). Furthermore, it serves as a trigger to accelerate the evolution of knowledge and contributes to innovative outcomes (Katila & Ahuja, 2002). What's more, the extent of originality is one of the proxies to distinguish innovation and imitation (Min et al., 2018; Wang & Jiang, 2020).

In all, the definition originality used in this article can be regarded as an attribute of knowledge which (a) departs from existing knowledge, (b) comes up with new ideas/methods/conclusions and other valuable output, or (c) stimulates further innovation.

Based on the criteria above for measuring originality, this study improved on the existing methods of knowledge combination, that is to say, evaluating the originality by constructed knowledge networks rather than just focusing on simple and direct knowledge combinations. In this way, the originality of various knowledge units was measured. Moreover, this study used textual features to identify the research field or object of a paper, as well as its research method and data sources. Therefore, the proposed method can give different weightings to different parts of a paper depending on the needs of specific evaluation and avoid using the same approach for different kinds of papers, which results in more reasonable assessments.

2.3. Existing measures of originality

Peer review is one of the most common approaches for evaluating originality (Feist, 2008; Shibayama & Wang, 2020) but with obvious drawbacks, such as subjectivity and personnel costs (Campanario, 1998). As researchers becoming more aware of the limitations of this method, together with recent advancements in computing ability and enriched bibliometric data, they begin to use computer technology to examine the specific contents of the papers. Several attempts have been made to measure the extent of originality of a particular paper by examining related indicators. These analyses can be divided into three major groups:

2.3.1. Analysis of knowledge components

Some scholars hold the view that the originality of knowledge components can represent a paper's level of originality. Keywords are the most common representatives of knowledge components. For instance, Azoulay et al. (2011) calculated the age of MeSH keywords, which are generated in the first year that an article is indexed by PubMed. And then scientific originality is measured through the age of keywords. The lower the age of a keyword, the more new ideas a paper has generated in a particular research field (Azoulay et al., 2011). Other researchers have tried to measure originality by calculating the occurrence and crossover rate of keywords (Lee & Su, 2010; Pflueger, 1991). However, although knowledge components do represent the core elements of a research paper, they do not reveal the full content of the theoretical background, methodology, data and results of a particular study.

2.3.2. Analysis of citation networks

A paper's citations can reveal its content. A number of scholars have therefore measured originality by examining the pattern of a paper's forward citations and references (Uzzi et al., 2013; Wu et al., 2019), focusing on the centrality of citation networks (Shibayama & Wang, 2020), structural network variations (Chen, 2006, 2012) and dynamic network structures (Funk & Owen-Smith, 2017). However, these approaches all focus on the intersectionality of the paper content, rather than on the originality of the content. Intersectionality may indicate originality to some degree, but it does not necessarily guarantee originality.

2.3.3. Analysis of knowledge combination

Several authors (Boudreau et al., 2016; Nelson & Winter, 1982) suggested that novelty represents a new or unusual combination of pre-existing knowledge components in a combinatorial perspective (Fleming, 2001; Kogut & Zander, 1992; Weitzman, 1996), and is considered as a proxy for originality (Ziman, 2003). Subsequent studies have operationalized knowledge components through keywords (Boudreau et al., 2016), referenced articles (Trapido, 2015), referenced journals (Wang et al., 2017) and entities (Foster et al., 2015). Although these methods evaluated papers from the perspective of originality, their limitation is that they only concentrate on new knowledge units while neglecting other knowledge properties, such as categories of knowledge. In addition, there are many combinations of knowledge units in a paper, so only focusing on combinations while ignoring the relationships between them can impede accurate analysis of the paper content.

In a broad sense, originality can refer to anything new, including new methods, theories, observations, hypotheses, or results (Shibayama & Wang, 2020). Recent approaches to the analysis of originality have compensated for some of the shortcomings of traditional external indicators, which have a time delay and cannot reflect the content of a paper. Some indicators based on content such as interdisciplinarity can also partly reflect originality. However, most content-based methods only provided a partial view of a paper's content. They were unable to identify all subject matter of a paper.

Given the drawbacks of the existing methods, we expanded the method of knowledge combination and proposed an approach for evaluating the originality of a paper based on the semantic network of its content. Firstly, we used dependency parsing to extract the knowledge units of papers. The sources of knowledge units were expanded from keywords to abstract, by which we not only expanded the scope of knowledge but also derived more complete knowledge units relative to keywords. Secondly, when combining knowledge, this study considered the semantic relationships between knowledge units rather than just simple and direct knowledge combinations. Differences between pairs of knowledge units will occur if there are different semantic relationships between them, even in the case of the same knowledge unit. Furthermore, we used a semantic similarity model, BERT, to obtain similar knowledge units. Similar knowledge units were then added to avoid calculation inaccuracies caused by those knowledge units with different shapes but same meanings. Finally, we assessed the originality of papers from Research Topics, Research Methods and Research Results, based on the connections between knowledge units.

3. Data and methods

In the following two sections we describe the data source we used and our proposed method for analyzing the originality of academic papers.

3.1. Data source

This study assessed the originality of papers in Library Science and Information Science (LIS). Abstracts from English-language papers in Q1 journals (identified by the JCR LIST 2021) in all disciplines published until 2014 were collected using Microsoft Academic Search, which were used as the corpus for the semantic links construction. In total, we retrieved more than 30 million papers involving 22 disciplines; the discipline distribution of the papers is shown in Appendix A-Table A1. To clarify the effectiveness of our proposed method for measuring originality, we also analyzed 3757 papers published in the *journal of informetrics (JOI), journal of information science (JIS), information processing & management (IPM), Scientometrics* and *journal of the association for information science and technology (JASIST)* between 2014 and 2018. Subsequently, to verify the universality of the proposed method, we selected 2015 papers from six journals including the *Journal of Educational Psychology, Journal of School Psychology, Journal of counseling Psychology, Child Development, Educational Psychologist* and *School Psychology Quarterly* in the field of Education Psychology and 3962 papers from three journals including *Electrochimica Acta, Carbon* and *Applied Surface Science* in the field of Carbon Nanotubes.

3.2. Method

We developed a method to evaluate the originality of paper content based on a knowledge unit network. The analysis process is as follows: (a) Collect papers in a certain discipline from the database. Obtain the abstracts of each paper after filtering out any papers with short abstracts or without an abstract. (b) Remove introductory sentences in the abstract and perform word segmentation and part-of-speech tagging on the remaining text. Conduct syntactic analysis to get the structural features of sentences and then extract the knowledge units and the relationships between them. (c) Use a semantic similarity evaluation model (such as the Word2vec and BERT models) to calculate the similarity between the knowledge units in a discipline. Build a semantic similarity model for knowledge units in each discipline. (d) Take the knowledge units as nodes. View the relationships between the highly correlated knowledge units as attributes of the edges. Thus construct the network of knowledge units. (e) Evaluate the abstracts of papers in line with the process in step (b) to identify the semantic links in the paper. (f) Calculate the connectivity of the semantic links in the knowledge unit network as an index for originality evaluation. In the following parts (b) to (f) are described in detail.

3.2.1. Extracting knowledge units and the relationship between them

This study used the natural language toolkit (NLTK) (Bird et al., 2009) and Stanford NLP (Manning et al., 2014) to explore knowledge units. For example, in the procession of sentence "We provide practical suggestions on in-house use data collection, collection development and weeding work", the first step to do is POS tagging. Next, lemmatization is performed, including tense and even word restoration. The tagging and lemmatization results are shown in Appendix A-Table A2. Then, dependency parsing of Stanford NLP was used on the processed data, which can lead to greater clarity of the sentence structures, allowing the relationships between the different parts to be observed.

The parts of NP (such as nouns-nouns, adjectives-nouns, present participle-nouns and past participle-nouns) form a knowledge unit. In our example, the following are knowledge units: "in-house use data collection", "in-house collection development", "in-house weeding work" and "practical suggestion." **"On" (IN), "and" (CC)** and **","** represent different relationships in knowledge units: **","** as well as **"and"** reveal the same connection between the knowledge units "in-house use data collection," "collection development," and "weeding work" knowledge units. **"On"** represents the determined relationship of "practical suggestion" in the "in-house use data collection," "in-house collection development," and "in-house weeding work" knowledge units. **"To"** indicates a progressive relationship among the various knowledge units, including verbs and prepositions denoting purpose (such as to, for). Finally, more than 1 million knowledge units were extracted from the corpus in the experiment.

3.2.2. Semantic similarity model between knowledge units

Traditional semantic similarity models used each word as a unit for similarity analysis. However, in most academic contexts, a single word cannot express all the relevant meanings. Simply dividing knowledge units without consideration of the relationship between knowledge units will cause semantic separation and fail to reveal the original meaning of knowledge. Therefore, in our proposed method we used a semantic similarity model focused on the relationship between knowledge units to extract knowledge units, which was involved in step (b). After knowledge units were separated, we used Sentence-BERT to compute the different kinds of semantic similarities between knowledge units.

The acronym BERT represents Bidirectional Encoder Representation from Transformers (Peters et al., 2017). The emergence of the BERT pre-trained language model has enhanced the development of natural language processing significantly, since by using pre-trained language model text representation ability can be acquired from a large-scale unsupervised corpus. That is, the BERT model has mitigated the disadvantages of previous models that had to learn on large-scale labeled data sets. In a similar manner to how the

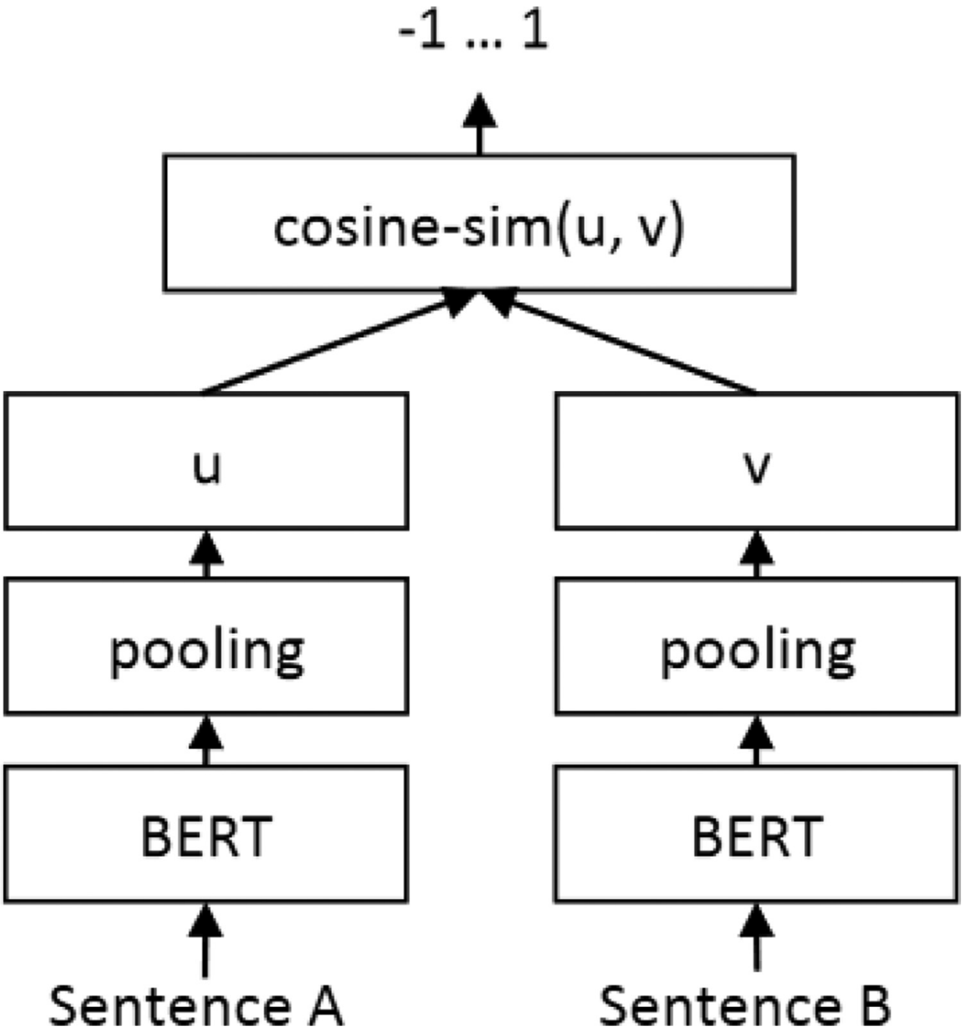

Fig. 1. Computation of the similarity score. In this calculation, we used cosine-similarity to measure the similarity between Sentences A and B (Reimers & Gurevych, 2019).

human brain learns. Effective results can be achieved using only simple fine-tuning in the downstream tasks. Sentence-BERT (Reimers & Gurevych, 2019) is an improved model based on BERT, which can greatly improve the speed of semantic similarity calculation by using the framework of the twin network model. Sentence-BERT adds a pooling operation to the output of BERT/RoBERTa to derive a fixed-size sentence embedding. It computes the mean of all output vectors and takes it as the sentence vector of the entire sentence, which not only guarantees the accuracy of the results but also improves the calculation speed. Sentence A and Sentence B were embedded by BERT and the cosine-similarity between the two-sentence embeddings u and v was computed (Fig. 1). The squared-error loss was used as the objective function. In our experiment, we set a batch size of 8, epoch of 4, Adam optimizer with learning rate of 3e−5, and a linear learning rate warm-up of over 10% of the training data.

The distribution of similarity in the present study is shown in Appendix B-Fig. B1.

3.2.3. The construction of knowledge unit networks

After the identification of the knowledge units and their inter-relationships in each sentence, the knowledge units were used as the nodes of the network. To reduce the computational cost, we specified that if the similarity between two knowledge units was greater than 0.6, they were considered highly similar. Each node was connected to highly similar knowledge units. The relationships between the knowledge units were considered edges. If the same knowledge unit groups had multiple relationships, the multiple connections were retained. Fig. 2 shows a knowledge unit network, where **A, B** and **C** are all knowledge units. The relationship between **A** and **B** is a unidirectional “TO” or “V” (verb pointing) connection. This reveals that **B** is in a progressive relation to **A** and is the purpose or result of **A**. There is a unidirectional “IN" relationship between **B** and **C**, indicating that **C** is a determining knowledge unit of **B**. For example, it might be connected to the location, time and means. Moreover, there is a bidirectional “CC” relation among **B**,

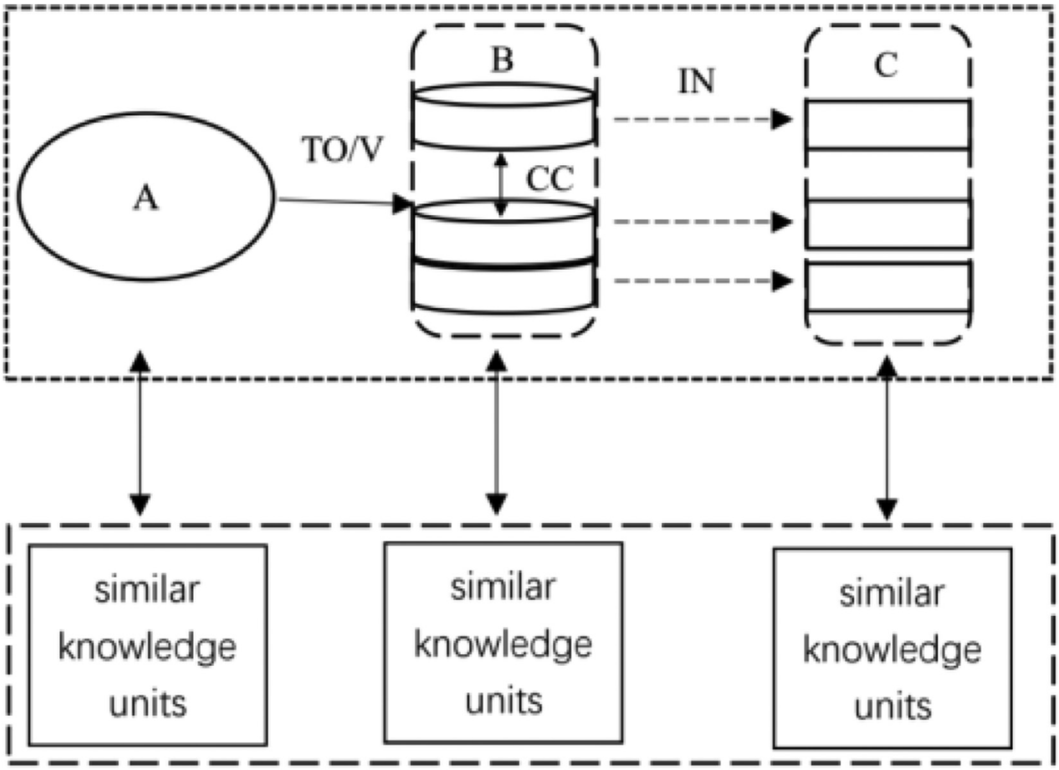

Fig. 2. Schematic diagram of the knowledge unit network.

demonstrating that the units of **B** are similar in nature. Each node contains other knowledge units that are highly similar to the unit in the network. The network is thus made up of knowledge units, relations and similar knowledge units.

3.2.4. Division of the abstract sentences

After manually annotating the features of papers in *JOI* published in 2018, we divided the semantic links into three parts, namely, Research Topics, Research Methods and Research Results. We then recorded the feature words and positions of the different categories, with the remaining data classified according to the similarity between the knowledge units and the tagged feature units and the position of the sentence.

3.2.5. Originality measurement

After the construction of the network, the knowledge unit links were extracted from each sentence in the paper. The knowledge links of the various sentences were integrated to form one or more knowledge links for the whole paper. Taking the knowledge links as the units of analysis, we calculated whether there were highly similar links in a given network. When there were similar links, we computed the specific similarity between the links and their corresponding knowledge units according to the semantic similarity model. Specifically, after the construction of the knowledge unit networks, all links in the corpus were used and the corpus was trained based on the Sentence-BERT model to obtain the semantic similarities between the links. The average similarity was taken as an indicator of the originality of the knowledge links in the paper. When multiple similar links occurred, the number of similar links and the similarity between those links were both recorded at the same time. Finally, taking each part of the paper as a unit of analysis (research topics, research methods, research results), we calculated the average number of similar links in each part and multiplied this by the average similarity. This provided the originality index for the paper. The higher the index number, the less originality was present in the paper. Lower index numbers indicated the presence of greater originality. Thus, we evaluated originality as follows:

$$O = \frac{\sum \mathrm{N.SLink} \times \mathrm{AVG.S}}{\mathrm{N.Link}} \tag{1}$$

Where O is originality; N.SLink represents the number of similar links in each semantic link; the Sentence-BERT model is used to calculate semantic similarity between each link and its similar link in the network; AVG.S refers to the average of each pair; N.Link refers to the sum of the links in the paper.

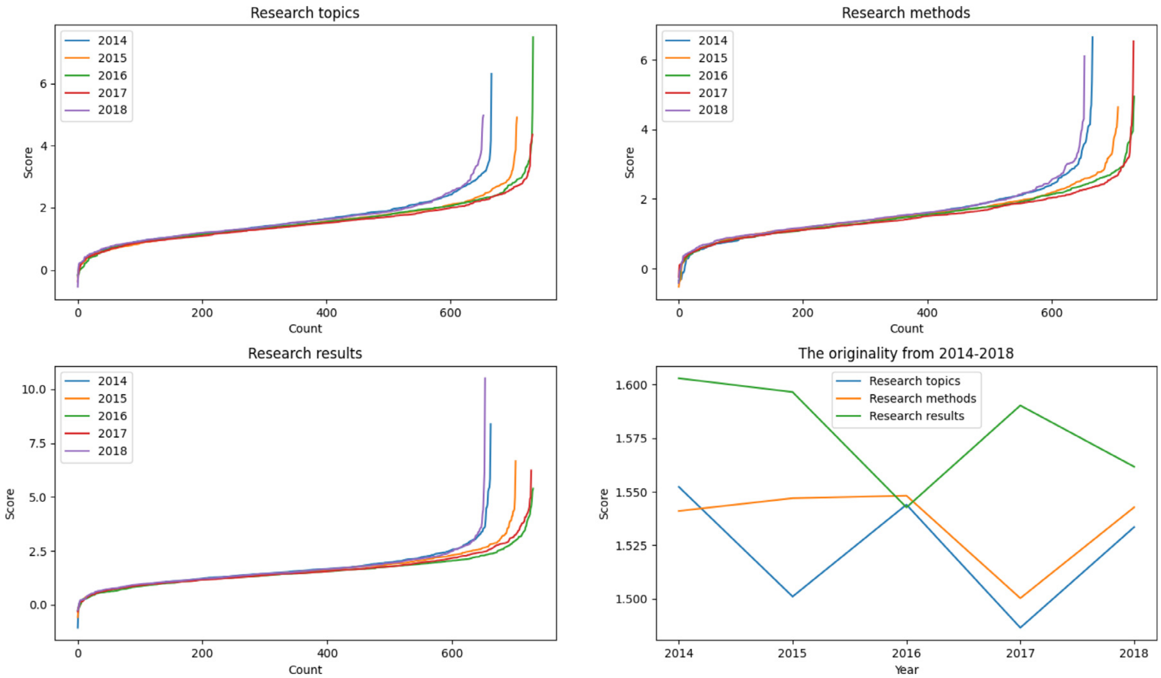

Fig. 3. Originality scores in Library & Information Science from 2014 to 2018.

4. Results and analysis

4.1. Results

We analyzed the abstracts of papers from five journals of LIS to calculate the originality scores of the semantic links in each abstract. We used feature words to label the attributes of different semantic links since different types of academic papers are original in different ways. The semantic links were divided into three categories: Research Topics; Research Methods; Research Results. In the specific evaluation process, the different parts were given different weights based on the type of paper. Table A3 in Appendix A shows a selection of the results (normalized by logarithm) regarding originality for papers published between 2014 and 2018.

The originality scores and their averages of the Research Topics, Research Methods and Research Results each year are shown in Fig. 3. A comparison of different data in the same year shows that the Research Results category had the highest originality index in most years, whereas the originality index was lowest for the Research Methods. This indicates that papers were most original in terms of their Research Methods, followed by their Research Topics and, finally, their results. In addition, all three sets of data show a roughly year-to-year downward trend.

To evaluate the effectiveness of the method and to compare the differences between papers with high and low originality, we used the LDA model to cluster the Research Topics, Research Methods and Research Results of the papers year by year. The LDA model is, at present, the most commonly used topic-clustering model (Blei et al., 2003). The model presumes that the words in the topic and the topics of the document are both subject to certain polynomial distributions. Hence, generating a document can be seen as a repeated process of selecting a topic with a certain probability and then selecting a word in the topic with a certain probability.

To obtain the best number of clusters, we used perplexity (Gruber et al., 2007) to evaluate the effectiveness of the trained model. After calculation, in the Research Topic category, the best number of topics was set to {89,81,89,79,79} from 2014 to 2018; in the category of Research Methods, this was {83,93,81,95,97}, while in the Research Results category, this was {91,71,75,91,77}. The originality of papers was then ranked from high to low and divided into ten equal parts. Then the number of topics in each interval and the number of papers on each topic were calculated and the results were plotted as shown in Fig. B2-B4. It was found that the nodes with high originality were smaller and more numerous than those with low originality. The Research Topics, Research Methods and Research Results all showed that the topic distribution of papers with high originality was more dispersed, while the topic distribution of papers with a low degree of originality tended to be more concentrated. In the low originality category, topics containing multiple papers are often apparent (the larger point on the graph).

Although the LDA model cannot be used to evaluate a single paper, its result of topic clustering presents the topic distribution for same papers. Because the research methods, theories and other parts of the papers with low originality are more similar to other papers, the number of clustering topics is smaller and the topics are more concentrated, while the papers with high originality are vice versa, which was verified by the experimental results, demonstrating the validity of the experiment to a certain extent.

4.2. Comparison with citation networks analysis

Uzzi et al. (2013) focused on rare combinations of journals cited by focal articles. In other words, if a paper cited documents in two journals that have been co-cited infrequently, it is regarded as a sign of novelty. Based on ten randomized citation networks constructed by a Monte Carlo algorithm, a Z-score can be generated (Eq. (2)) for each journal pair. Finally, Uzzi et al. (2013) used the Z-score for that paper to measure the novelty.

$$Z score = \frac{(obs - exp)}{\sigma} \tag{2}$$

Where *obs* is the observed frequency of the journal pair in focal papers, while *exp* is the mean and σ is the standard deviation of the number of journal pairs obtained from the 10 randomized cases.

Based on existing methods in measuring the originality of papers and patents, Wu et al. (2019) proposed the Disruption index (DI) for scholarly citation data. According to its definition, if the subsequent papers of a paper coincided with the references of that paper, it was considered that the knowledge had been inherited and consolidated. In contrast, if the paper created a new research path, it was considered disruptive. The DI and the originality are related, and the DI can also reflect articles' originality to some extent.

Papers can be coupled when both they and their references are cited in one paper. Thus, the stronger the continuity by bibliographic coupling in the citation generation, the lower the disruption and originality.

$$DI = \frac{N_F - N_B}{N_F + N_B + N_R} \tag{3}$$

Where N_B is the number of papers citing both the focal paper (FP) and at least one of its references; N_F is the number of papers citing the FP exclusively and not one of its references; N_R is the number of papers citing references of FP.

This study calculated the Z-score as well as the DI and compared them with our method. The papers were ranked by their originality score from top to bottom in the three categories and were then divided into 10 equal parts. A boxplot was used to analyze the relationship between originality and the two indicators. As shown in Figs B5 and B6, it can be seen that there is no obvious relationship between the two indicators and the originality proposed by this study. For one thing, a novel idea may not necessarily be reflected in the reference it may come from discussions with colleagues or interdisciplinary exchange (Tahamtan & Bornmann, 2018; Bornmann et al., 2019b). For another, the methods do not emphasize the knowledge itself (Shibayama & Wang, 2020), while unconventional journal or reference combinations may indicate interdisciplinary research rather than originality (Porter et al., 2006; Zhang et al., 2016).

4.3. Comparison with knowledge combination

New or unusual knowledge combinations are also indicators of a paper's originality (Nelson & Winter, 1982). Previous studies have combined keywords or knowledge units to assess the originality of papers (Boudreau et al., 2016; Foster et al., 2015; Yan et al., 2020). In this paper, we compared our method with the method proposed by Yan et al. (2020). The details are summarized as follows:

The research (Yan et al., 2020) proposed a novel method to measure new combinations. They considered that new combinations in a paper are measured by new keyword pairs in related research areas over the previous five years. This is, thus, an indicator created by using the paper keywords. A paper's new combinations will be calculated as follows:

$$\text{new combinations}_{\text{i}} = \frac{\sum_{\text{j}=1}^{\text{N}_\text{i}} x_j}{C_{N_i}^2} \tag{4}$$

where x_j is a binomial variable. If the keyword pair combination has never appeared in papers in the previous five years in the LIS, $x_j = 1$, otherwise $x_j = 0$. $C_{N_i}^2$ refers to all combinations of keyword pairs in the paper. The new combinations in a paper were defined as the ratio of new combinations of keyword pairs to all potential combinations of keyword pairs. The pair formed by a previous element and a new element was considered to represent a new combination.

The new knowledge combinations of papers in five journals were calculated and the score was compared with the score calculated by the method proposed in the present study. The same method as 4.2 was also used to analyze the relationship between them. As shown in Fig. B7, since the method of the current study represents an improved version of this type of method, the difference between the above two comparisons can be seen in the relation comparison. In the Research Methods and Research Results categories, the originality calculated by the method proposed in the current study showed no obvious correlation with the originality scores calculated by knowledge combinations. While in Research Topics, a positive correlation between the two methods was observed, with decreasing originality calculated by the method proposed in this study correlating with decreasing originality calculated by the knowledge combination method.

The main reason for these results is that most keywords represent Research Topics with only a few representing Research Methods and Research Results. This would account for the observed correlation between the originality of the keyword-based knowledge combination method and the originality calculated in this study for Research Topics. The use of keywords is a limitation of this method as many papers have the same score and some papers, such as those published in *JASIST*, do not have keywords. This would be inconvenient for practical use and would create problems such as insufficient differentiation and limited scope of measurement. In addition, the direct combination of knowledge units may lead to problems such as repetition and the inclusion of irrelevant words in the components. For example, the paper entitled "On a formula for the h-index" (Bertoli-Barsotti & Lando, 2015) includes "citation

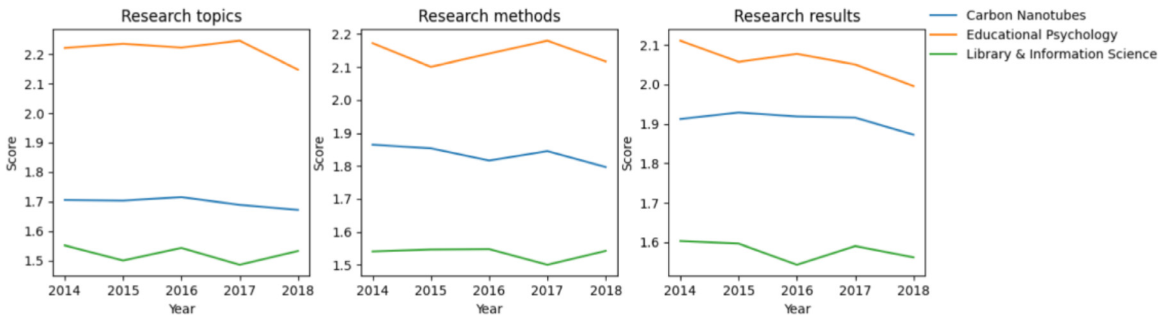

Fig. 4. Comparison of originality in three disciplines.

data" and "citation statistic" as two keywords. However, it does not make sense to calculate the frequency of components that are repetitive. Both "scientometrics" and "citation analysis" are keywords in "More precise methods for national research citation impact comparisons" (Fairclough & Thelwall, 2015). However, the connotations of the former contain the latter, so it is unreasonable to evaluate its level of originality by focusing purely on its keywords. Moreover, the question of whether keywords truly and comprehensively reflect the content of a paper is a matter which needs for further discussion. All of these aspects are disadvantages of the method of keyword combinations.

4.4. Comparison between disciplines

The semantic network was built by knowledge units from all disciplines, which allowed it to be used to measure originality in a variety of disciplines. To examine the effectiveness and universality of the method proposed in this paper, we chosed a similar number of papers from two disciplines, Educational Psychology and Carbon Nanotubes, and calculated their originality scores. The average score for each year was compared with the score of papers in LIS. The results in these three completely different disciplines are shown in Fig. 4.

It can be seen from the figure that the originality of papers in all three disciplines tended to increase over time. Nevertheless, differences between the three disciplines were apparent: while the originality of the Research Results in Carbon Nanotubes increased sharply, other trends are less obvious, such as the Research Topics in LIS and the Research Methods in Carbon Nanotubes. Moreover, the ranges of the originality scores in the different disciplines differ. The originality of Library & Information Science is highest, followed by Educational Psychology, and the lowest originalityis seen in Carbon Nanotubes.

These differences result from the specific attributes of the disciplines. Carbon Nanotubes falls under engineering and Education Psychology at the intersection between natural and social science, while Library & Information Science is a social science. Different disciplines have different research paradigms, leading to different emphases in research. In comparison, the engineering paradigm is more stable while that of social science is more varied and purposeful (Heilbron, 2003; Wang & Yin, 1996). Furthermore, the difference in the score distributions is related to the scale. According to the search results from the Web of Science, while numbers of papers in the Education Psychology and Library & Information Science are approximately 50 thousand and 80 thousand, respectively, the number of published papers in the field of Carbon Nanotubes is over 200 thousand. The higher the number of academic publications, the higher the proportion of its knowledge in the entire knowledge network, resulting in more similarities and more knowledge links, leading to higher scores.

4.5. Comparison of high scientific quality and originality

To investigate a more objective method to verify the effectiveness of existing methods for determining paper originality, we selected papers that had been recognized as having high scientific quality or originality in the fields of Carbon Nanotubes and Educational Psychology from 2014 to 2018. These included Nobel Prize-winning papers, papers published in *Nature* and *Science*, and those sharing features representing the most advanced research with significant potential for high impact in the field and identified by MDPI. Four methods for measuring originality were then applied and compared. To avoid biases associated with discipline and time, we used percentages instead of scores for comparisons. After exclusion, we obtained 59 papers (27 papers published in *Nature* and *Science,* 29 feature papers and 3 Nobel Prize-winning papers). The comparative results are shown in Fig. 5 and the details are described in Table A4. We used the percentile rather than the real value to contrast and have highlighted the top of the six indicators in italic and bold fonts in Table A4. Due to missing data in several Nobel Prize-winning papers, we were unable to calculate some indicators.

The comparison and analysis show that the scores calculated by the three methods don't always result in high ranking in the same fields, in contrast to the score calculated by the method proposed in the current study where higher rankings are obtained. In addition, the originality of the Research Topics is found to be highest, followed by Research Methods, and the originality of Research Results is the lowest.

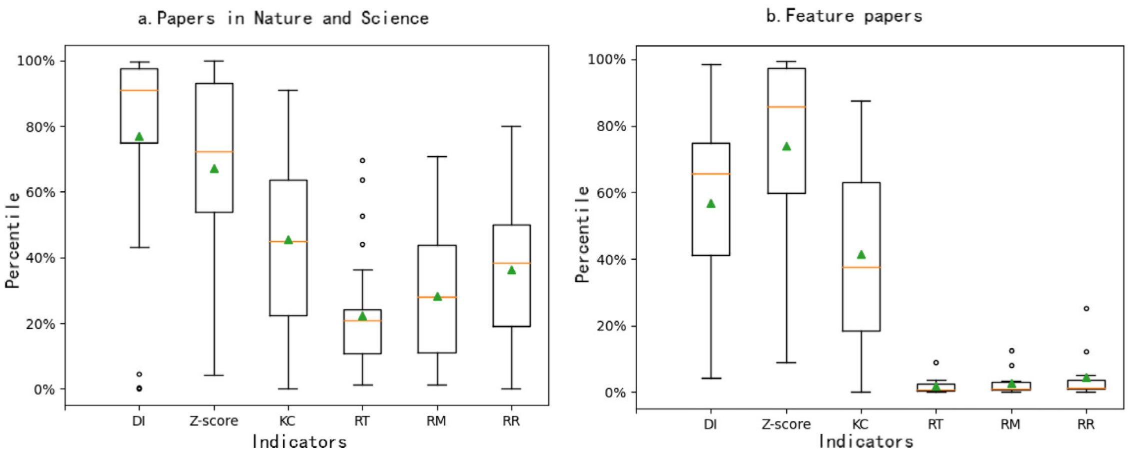

Fig. 5. Comparison of scores of different indicators in selected papers. DI, Disruption Index proposed by Wu et al. (2019); Z-score as proposed by Uzzi et al. (2013); KC, indicator of keyword combinations; RT, Research Topics; RM, Research Methods; RR, Research Results.

As described above, the formation of a citation network does not necessarily relate to knowledge. Therefore, when using the citation network method, the Z-score and DI are not necessarily high, while the use of keywords is not accurate and does not directly reflect the content. Compared with other methods, the method proposed in this study can not only measure originality more accurately but can also measure the different parts of papers separately.

5. Discussion and conclusions

Other researchers have pointed out the shortcomings of using citations to assess the quality of academic papers (Abramo, 2018; Baird & Oppenheim, 1994; MacRoberts & MacRoberts, 1989; Brooks, 1986). In response, scholars have gradually come to recognize that external index can only represent the impact of a paper rather than its quality (Abramo, 2018; Ozanne et al., 2017) and tried to evaluate quality in other ways. One of the most important methods of measuring quality is by assessing originality (Gaston, 1973). There are clear differences in the definition and measurement of originality and impact, with originality representing an inherent quality of a scientific paper while impact depends on other factors. Based on this view, we have redefined the concept of originality and differentiated it from similar concepts.

Unlike traditional measurements based on impact, many researchers have evaluated quality based on the content of papers, for example by the use of keywords, the citation structure method and the new knowledge unit method (Lee & Su, 2010; Pflueger, 2005; Boudreau et al., 2016; Shibayama & Wang, 2020). However, these methods have certain limitations. For example, the keywords and knowledge units only reflect part of a paper's content. They are decided upon by the authors themselves without objective regulation. Moreover, some keywords or knowledge units cannot be viewed as separate and distinct, such as scientometrics and citation analysis, meaning that the calculation of statistic frequency or component frequency may lead to inaccurate results.

This study used paper abstracts to construct semantic networks in the light of the semantic relations between knowledge units. This helped to avoid the problem of using single keywords or knowledge units that might only partially reflect a paper's content. To deal with the lack of standardization of keywords and knowledge units, the abstracts of LIS papers were used as a training set to obtain semantic similarity between knowledge units. When evaluating the papers, we extracted semantic links from their abstracts and calculated their connectivity within a subject-specific semantic network. This provided the original score for the semantic links. After that, we divided the semantic links into three types: Research Topics, Research Methods and Research Results. This enabled us to arrange the weight of the corresponding part according to the research focus of particular studies.

We selected papers published in three disciplines from 2014 to 2018 as our experimental sample. Our results showed that originality increased with time. To verify the effectiveness of the method, we used the LDA model to cluster the topics of papers. The results showed a decline in the topic concentrations together with a decline in originality. Papers with high originality tend to include more topics than those with lower originality, which verifies the effectiveness of our method.

We also compared the proposed method with the citation network and keyword combination methods for evaluating originality. Overall, there was no obvious correlation between the results of the three other methods and the method used in this study (the correlation analysis is shown in Table A5). However, compared with the other two methods, the results of knowledge combination correlated positively with the method proposed in this study in the category of Research Topics. We identified several problems with the three other methods. For example, the number of citations a paper receives is affected by many factors, so the citation network constructed based on citations will also be affected by many non-knowledge factors. In addition, novel ideas or knowledge may not be reflected in references and the method based on citation networks emphasized atypical journal pairs while neglecting the knowledge itself (Shibayama & Wang, 2020). Furthermore, the selection of keywords is completed by the authors themselves, resulting in the chaotic relationships between keywords, with many keywords reflecting the authors' topics while ignoring other parts of the research. The shortcomings of these methods explain why most of the results they produce do not correlate with the results gleaned from our proposed method for measuring originality. Both the consequences of our experiment and this comparison demonstrate the characteristics of our method and verify its effectiveness.

To verify the universal applicability of this method, we added similar numbers of papers from the fields of "educational psychology" and "carbon nanotubes" and compared their originality scores along the time dimension. Overall, the originality in the three disciplines tend to increase with time. However, because of the different characteristics and sizes of the three disciplines, both the magnitude of change and the ranges of their originality scores varied. In addition, we compared the results of four methods for measuring papers with high originality, and the results showed that compared with existing methods, the method proposed here is more universally applicable and more directly related to content's originality.

Nevertheless, there are certain limitations to the approach followed in this study:

(1) The study did not assign weight to different categories according to the types of papers. There were no differentiations between reviews, methodological papers and theoretical papers. However, different types of papers may differ in terms of their Research Topics, Research Methods and Research Results. In subsequent studies, various weights could be given to different paper types when calculating originality.
(2) In addition to the Research Topics, Research Methods and Research Results, the contents of research papers also include research data and other information. In future research, more granular classification is needed.

Author statement

We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled "A New Method for Measuring Originality of Academic Article Based on Knowledge Units in Semantic Networks".

CRediT authorship contribution statement

Jianhua Hou: Conceptualization, Methodology, Writing – review & editing. **Dongyi Wang:** Data curation, Writing – original draft. **Jing Li:** Supervision, Validation.

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Appendix A. Table

Table A1
Overview of disciplines included in the whole corpus.

Research categories	Publications	Number of knowledge units
Agricultural Sciences	24,571	73,022
Arts & Humanities, Interdisciplinary	15,060	44,757
Biology & Biochemistry	314,582	934,919
Chemistry	283,824	843,507
Clinical Medicine	498,579	1,481,745
Computer Science	92,881	276,038
Economics & Business	106,272	315,835
Engineering	321,225	954,662
Environment/Ecology	121,540	361,211
Geosciences	72,316	214,917
History & Archaeology	19,897	59,132
Literature & Language	20,756	61,686
Materials Science	221,281	657,633
Mathematics	84,056	249,809
Multidisciplinary	447,424	1,329,715
Philosophy & Religion	15,609	46,390
Physics	365,280	1,085,589
Plant & Animal Science	86,257	256,351
Psychiatry/Psychology	65,724	195,328
Social Sciences, General	166,367	494,433
Visual & Performing Arts	21,307	63,322

Table A2
Tagging and restoration results of the example.

Vocabulary	Part of speech	Prototype
We	PRP	We
provide	VB	Provide
practical	JJ	Practical
suggestions	NN	Suggestion
on	IN	On
in-house	NN	in-house
use	NN	Use
data	NN	Data
collection	NN	Collection
,	,	,
collection	NN	Collection
development	NN	Development
and	CC	And
weeding	NN	Weeding
work	NN	Work

Note: PRP=personal pronouns, JJ=adjectives, NN=nouns, VB=verb, IN=prepositions or subordinator, CC=conjunctions.

Table A3
Partial originality evaluation results for papers published from 2014 to 2018.

Title	Research topics	Research methods	Research results
Evaluation of websites' compliance to legal and ethical guidelines: A fuzzy logic–based methodology	0.23347	2.455714	2.549428
PSI: A probabilistic semantic interpretable framework for fine-grained image ranking	0.324075	0.509548	1.921161
Emergent structures in faculty hiring networks, and the effects of mobility on academic performance	0.47707	0.887598	1.311523
Tracing the traces: The critical role of metadata within networked communications	0.903851	0.855331	1.53755
Predictive models and analysis for webpage depth-level dwell time	0.939146	0.205179	1.157274
Fast prediction of web user browsing behaviors using the most interesting patterns	0.969403	1.29881	1.326717
Understanding scientific collaboration: Homophily, transitivity, and preferential attachment	1.215362	2.011465	1.285733
Using computer vision techniques on Instagram to link users' personalities and genders to the features of their photos: An exploratory study	1.313514	1.272175	1.220668
The change from an eponym to a representative name: Wegener to granulomatosis with polyangiitis	1.895211	2.179091	0.640056
Relationship between international collaboration papers and their citations from an economic perspective	2.574917	4.298913	3.794411
Global analysis of the E-learning scientific domain: a declining category?	2.734974	2.75179	2.696076
Pros and cons of the new financial support policy for Turkish researchers	2.77933	2.3423	1.229524
The co-evolution of knowledge and collaboration networks: the role of the technology life-cycle	3.74609	1.583358	2.675646
The lognormal distribution explains the remarkable pattern documented by characteristic scores and scales in scientometrics	3.879276	1.88647	1.841476
Discontinuities in citation relations among journals: self-organized criticality as a model of scientific revolutions and change	4.477849	3.027451	1.522012
A quantitative analysis of determinants of non-citation using a panel data model	4.878411	4.211928	4.2168

Table A4
Comparison of scores of different indicators in selected papers.

Source	ID	DI	Z-score	KC	RT	RM	RR
NS	1	96.30%	99.43%	59.27%	***1.49%***	70.70%	26.99%
NS	2	99.74%	44.85%	69.78%	15.97%	51.29%	***14.38%***
NS	3	95.98%	65.98%	14.36%	44.15%	51.50%	***0.96%***
NS	4	***0.23%***	66.63%	36.07%	23.04%	4.32%	18.55%
NS	5	98.00%	85.11%	***12.96%***	63.65%	69.09%	67.33%
NS	6	***4.52%***	61.71%	75.21%	36.35%	32.84%	38.36%
NS	7	89.51%	87.27%	88.81%	***10.35%***	14.76%	40.99%
NS	8	97.33%	89.80%	59.27%	24.88%	***5.17%***	42.13%
NS	9	97.73%	98.61%	50.78%	***13.18%***	57.87%	74.67%
NS	10	88.06%	99.49%	63.54%	***4.96%***	32.89%	23.82%
NS	11	91.15%	10.00%	39.61%	52.69%	***29.34%***	38.75%
NS	12	89.92%	81.88%	30.67%	***22.71%***	27.50%	45.32%
NS	13	78.72%	52.88%	14.14%	23.19%	2.03%	***0.14%***

(*continued on next page*)

Table A4 (*continued*)

Source	ID	DI	Z-score	KC	RT	RM	RR
NS	14	82.99%	99.82%	55.98%	***20.89%***	42.13%	61.45%
NS	15	91.30%	27.53%	***0.00%***	19.37%	45.90%	79.37%
NS	16	99.47%	99.59%	63.74%	***10.83%***	17.89%	41.67%
NS	17	98.21%	96.26%	13.61%	***21.70%***	27.99%	79.95%
NS	18	91.62%	97.17%	33.92%	18.50%	***7.53%***	19.59%
NS	19	78.36%	56.29%	35.72%	10.78%	***4.23%***	22.99%
NS	20	92.44%	10.31%	84.62%	21.12%	***1.41%***	16.23%
NS	21	98.49%	71.02%	31.35%	***10.64%***	12.59%	70.15%
NS	22	71.79%	72.56%	90.96%	36.06%	14.54%	***6.00%***
NS	23	98.05%	89.59%	10.16%	***3.02%***	20.48%	19.47%
NS	24	***0.52%***	21.29%	53.64%	1.35%	33.76%	54.69%
NS	25	47.71%	72.24%	91.15%	***21.00%***	31.06%	44.66%
NS	26	43.32%	54.97%	45.11%	***6.73%***	45.54%	33.98%
NS	27	59.07%	4.27%	9.46%	69.59%	9.82%	***0.45%***
Feature	28	48.93%	81.44%	63.64%	***0.31%***	1.00%	12.09%
Feature	29	78.67%	98.06%	31.25%	0.53%	0.85%	***0.16%***
Feature	30	null	31.05%	31.25%	0.14%	***0.06%***	0.24%
Feature	31	null	44.44%	90.91%	1.81%	***0.60%***	1.47%
Feature	32	null	86.91%	31.25%	1.21%	***0.40%***	1.80%
Feature	33	4.39%	70.59%	18.75%	***0.10%***	7.97%	25.09%
Feature	34	91.08%	99.27%	18.18%	0.70%	0.88%	***0.38%***
Feature	35	null	33.73%	75.00%	***0.20%***	1.59%	0.23%
Feature	36	null	9.03%	6.25%	***2.15%***	3.07%	9.43%
Feature	37	null	9.03%	31.25%	0.37%	***0.03%***	0.05%
Feature	38	null	48.80%	18.75%	0.44%	0.37%	***0.02%***
Feature	39	14.54%	9.03%	62.50%	***0.53%***	12.56%	1.09%
Feature	40	null	73.33%	81.25%	1.32%	0.99%	***0.89%***
Feature	41	null	93.47%	25.00%	***0.04%***	3.40%	0.61%
Feature	42	53.06%	97.40%	37.50%	0.45%	***0.19%***	2.28%
Feature	43	null	21.37%	0.00%	1.35%	1.73%	***0.01%***
Feature	44	null	7.27%	50.00%	***0.71%***	4.77%	1.48%
Feature	45	null	82.50%	43.75%	0.38%	***0.33%***	1.89%
Feature	46	null	52.33%	87.50%	3.04%	***0.47%***	3.58%
Feature	47	98.41%	90.90%	56.25%	3.63%	3.33%	***1.24%***
Feature	48	33.40%	48.97%	68.75%	1.28%	***0.52%***	1.07%
Feature	49	null	36.94%	12.50%	***2.99%***	6.11%	9.49%
Feature	50	null	38.07%	81.82%	***0.58%***	2.36%	3.48%
Feature	51	null	85.89%	null	1.47%	7.31%	***0.02%***
Feature	52	null	84.31%	null	3.23%	2.56%	***0.89%***
Feature	53	null	50.69%	72.73%	11.14%	12.95%	***1.34%***
Feature	54	65.69%	85.76%	87.50%	9.10%	***1.14%***	1.40%
Feature	55	70.81%	33.37%	12.50%	0.82%	***0.77%***	5.10%
Feature	56	66.06%	97.42%	0.00%	3.65%	2.72%	***1.25%***
Nobel Prize	57	null	20.11%	null	***13.22%***	21.60%	43.75%
Nobel Prize	58	null	63.13%	null	20.44%	***1.00%***	46.72%
Nobel Prize	59	null	26.90%	null	46.34%	***22.13%***	41.46%

Note: NS = papers published in *Nature* and *Science*, Feature = Feature papers, Nobel Prize = Nobel Prize-winning paper. To compare the differences between the indicators directly, the score-ranking percentage of the papers in the same field and the same period was used instead of the specific index score. Numbers in italic and bold font indicate that the index score is higher than that of the other indicators.

Table A5
Correlation analysis between indicators.

Correlation analysis		Z-score	KC	DI
RT	Pearson correlation	0.003	−0.059**	−0.019
	Sig. (2-tailed)	0.874	0.001	0.358
	N	3496	2962	2252
RM	Pearson correlation	0.017	−0.006	0.001
	Sig. (2-tailed)	0.306	0.736	0.977
	N	3496	2962	2252
RR	Pearson correlation	0.003	−0.01	−0.024
	Sig. (2-tailed)	0.837	0.592	0.262
	N	3479	2953	2249

Note: RT, Research Topics; RM, Research Methods; RR, Research Results; Z-score, the indicator proposed by Uzzi in 2013; KC, the indictor based on knowledge combination; DI, Disruption Index proposed by Wu in 2019.

** Correlation is significant at 0.01 level(2-tailed).

Appendix B. Figure

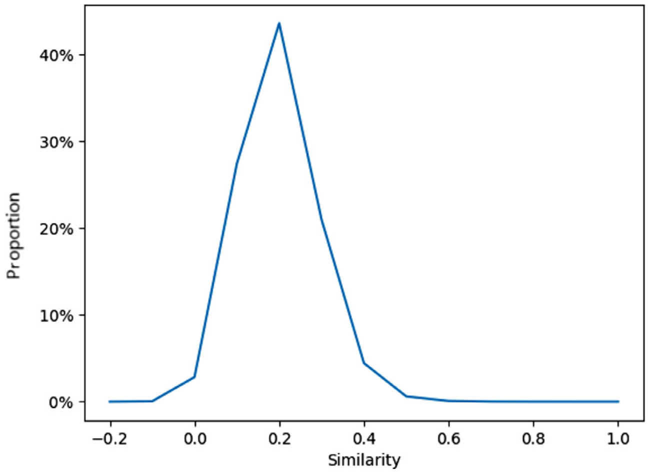


Fig. B1. The distribution of similarity. Similarities between each word and other words were calculated. Each line reflects the distribution of similarity between one word and the other words.

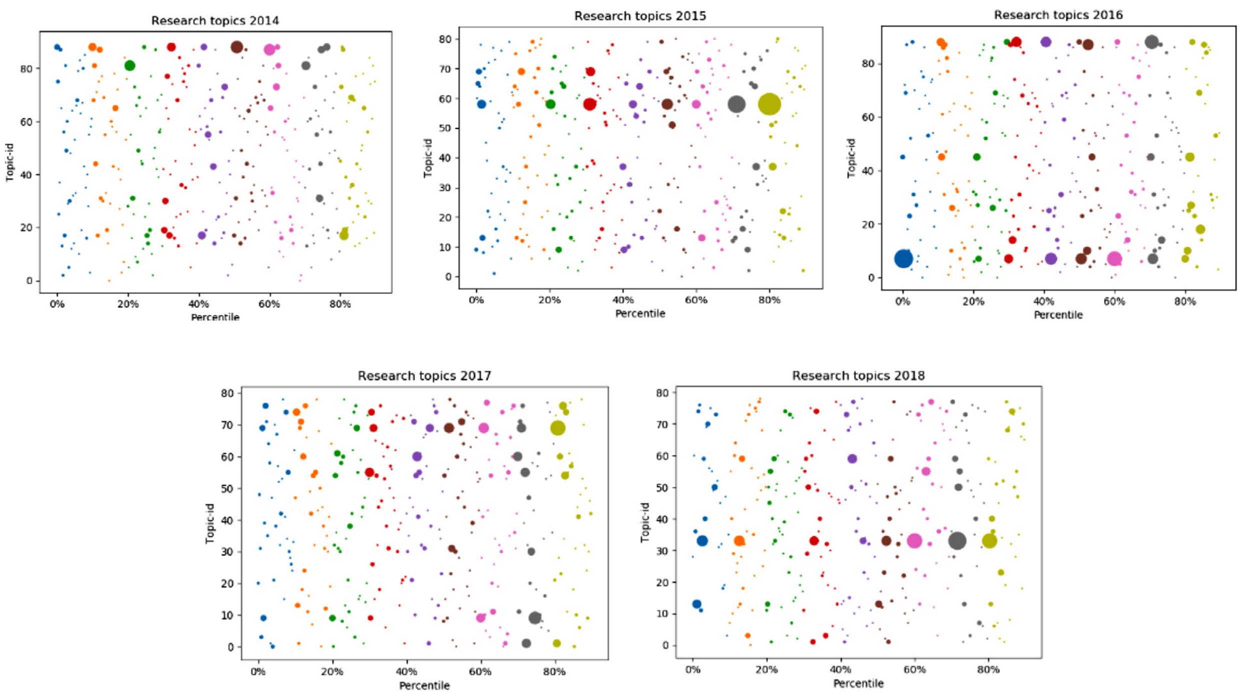


Fig. B2. Topic clustering in research topics. In Fig. A1-A3, there are 10 colored nodes and each color contains 10% of the papers within a year. Different node colors reflect different degrees of originality; the originality is reduced from left to right. Node sizes are based on the number of texts within the topic cluster. The larger the node, the greater the number of papers on the topic.

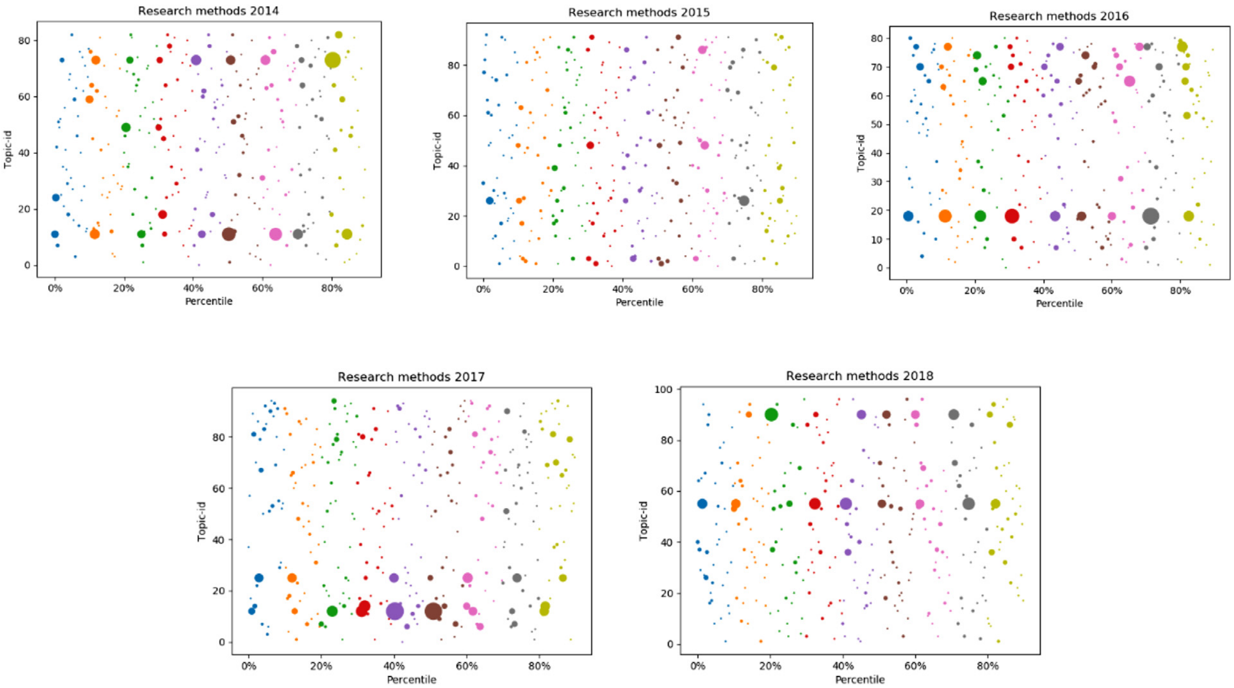


Fig. B3. Topic clustering in research methods.

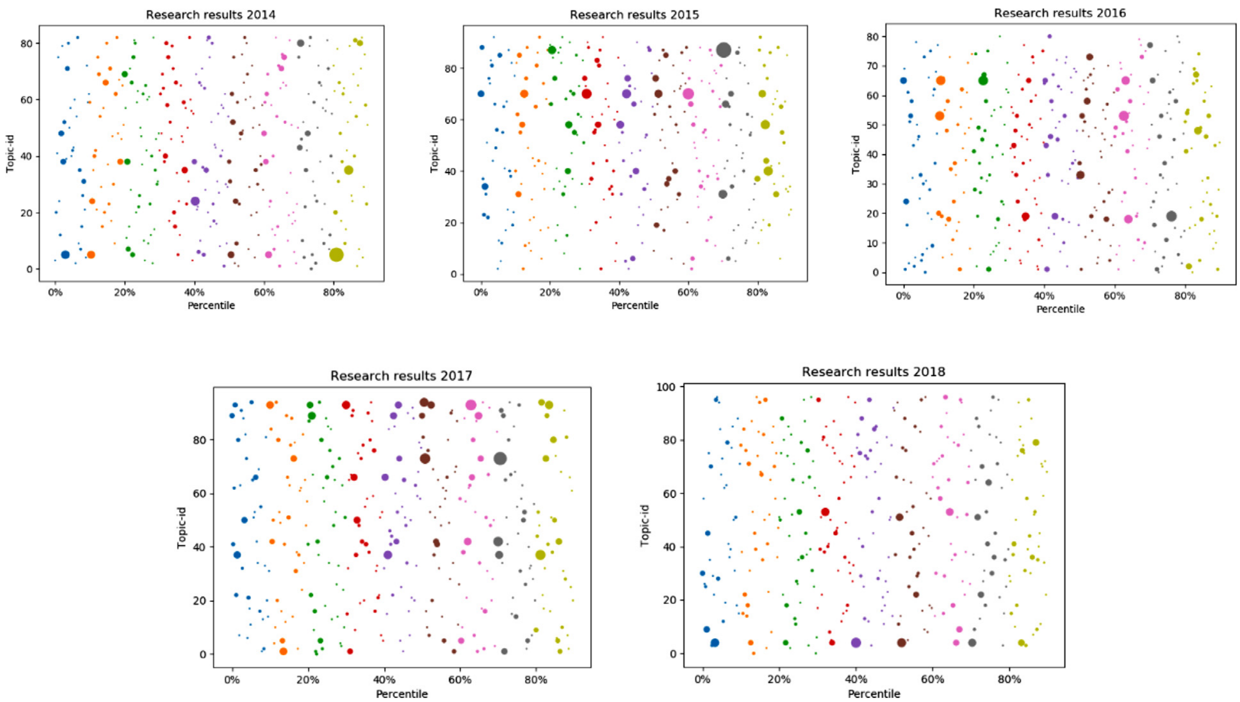


Fig. B4. Topic clustering in research results.

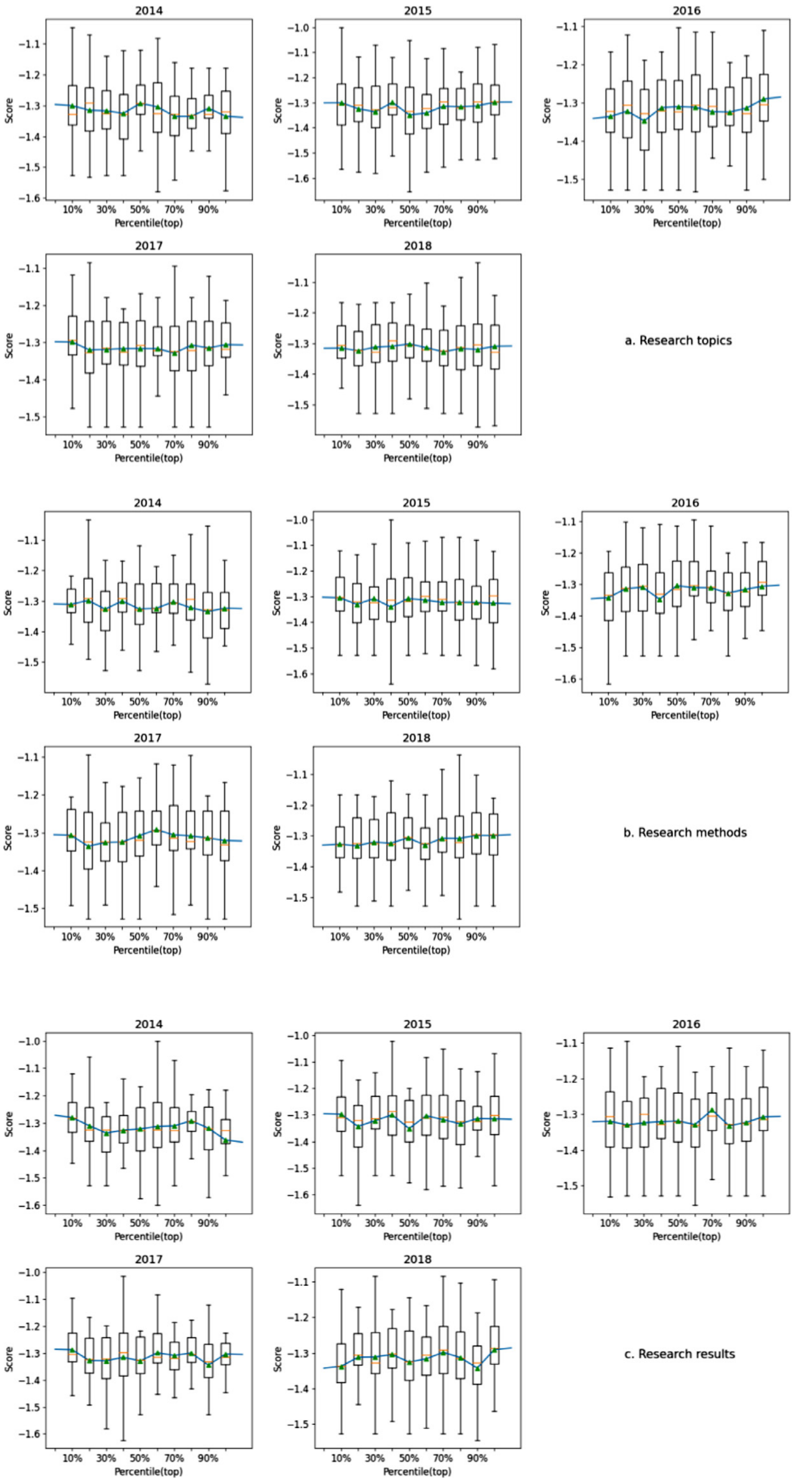


Fig. B5. The relationship between originality and citation networks. In Fig. A5-A7, papers were ranked according to originality score from top to bottom and were then divided into 10 equal parts. The boxplot was used to analyze the relationship between the parts and the score. The X-axis indicates the distribution of originality, from top 10% to bottom; the Y-axis indicates the Z-score.

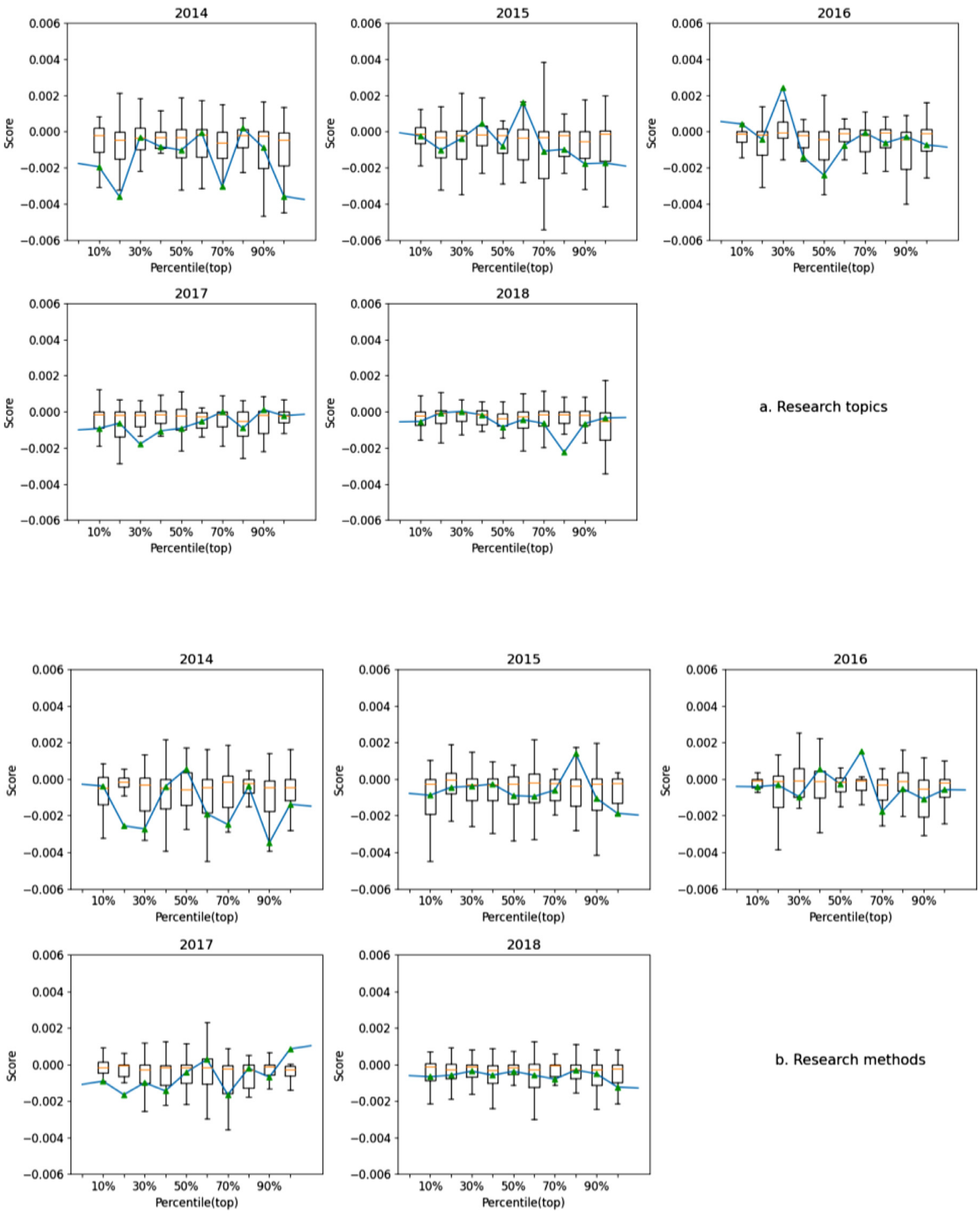


Fig. B6. The relationship between originality and Disruption Index. The X-axis represents the distribution of originality, from top 10% to bottom; the Y-axis represents the Disruption Index score.

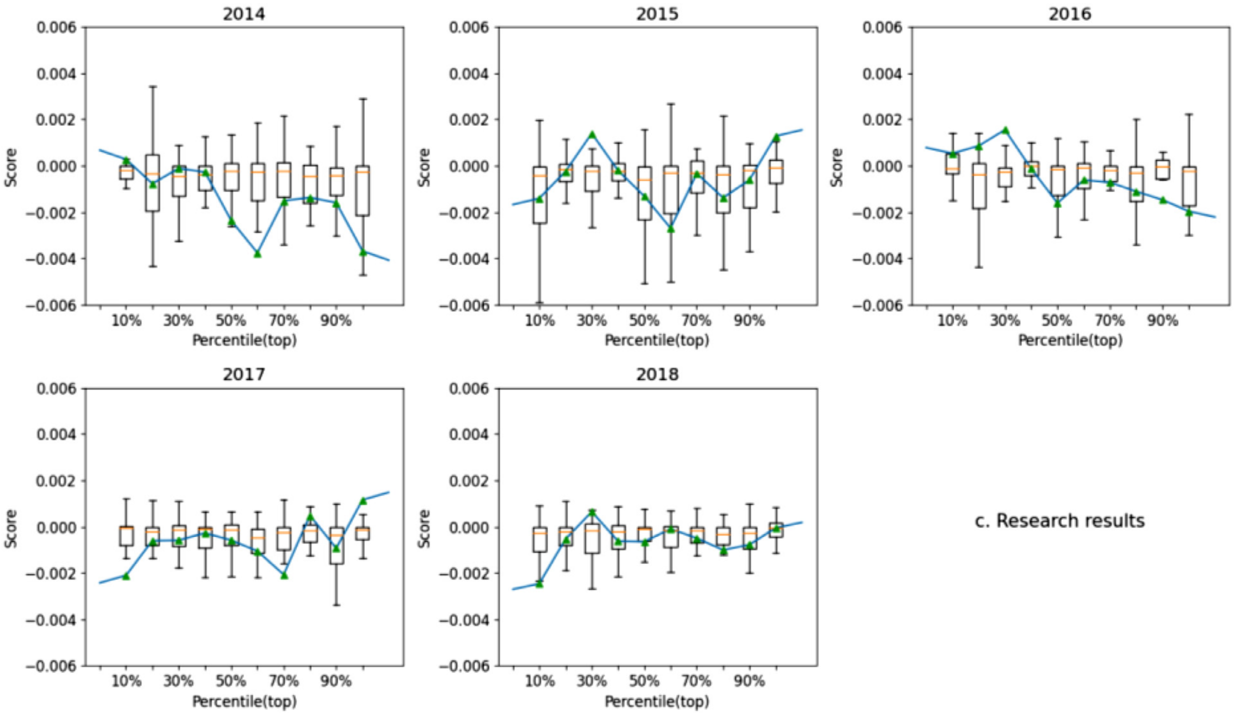


Fig. B6. Continued

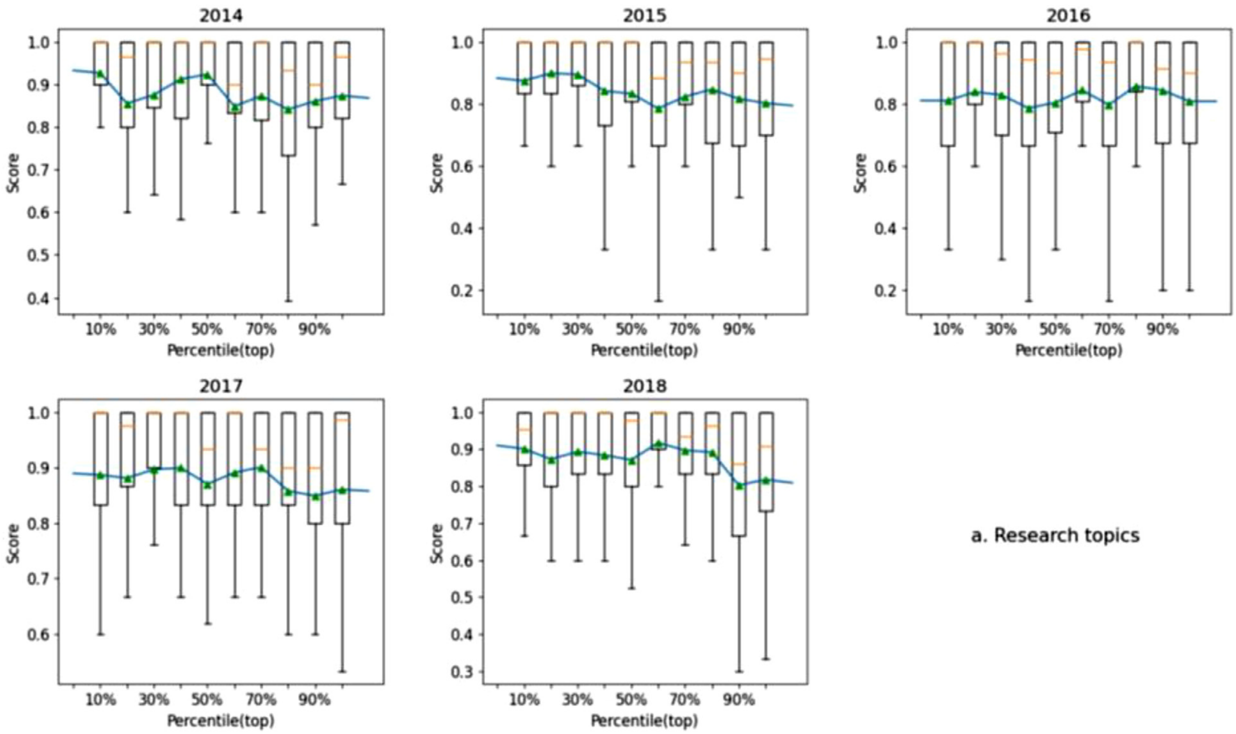
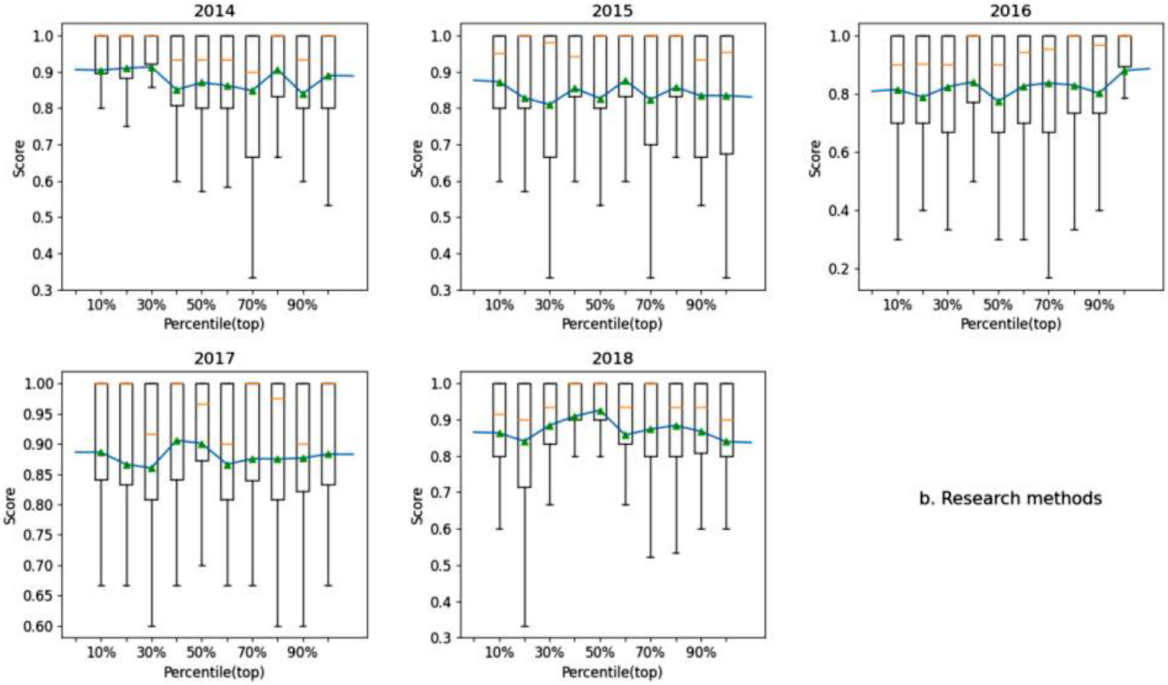
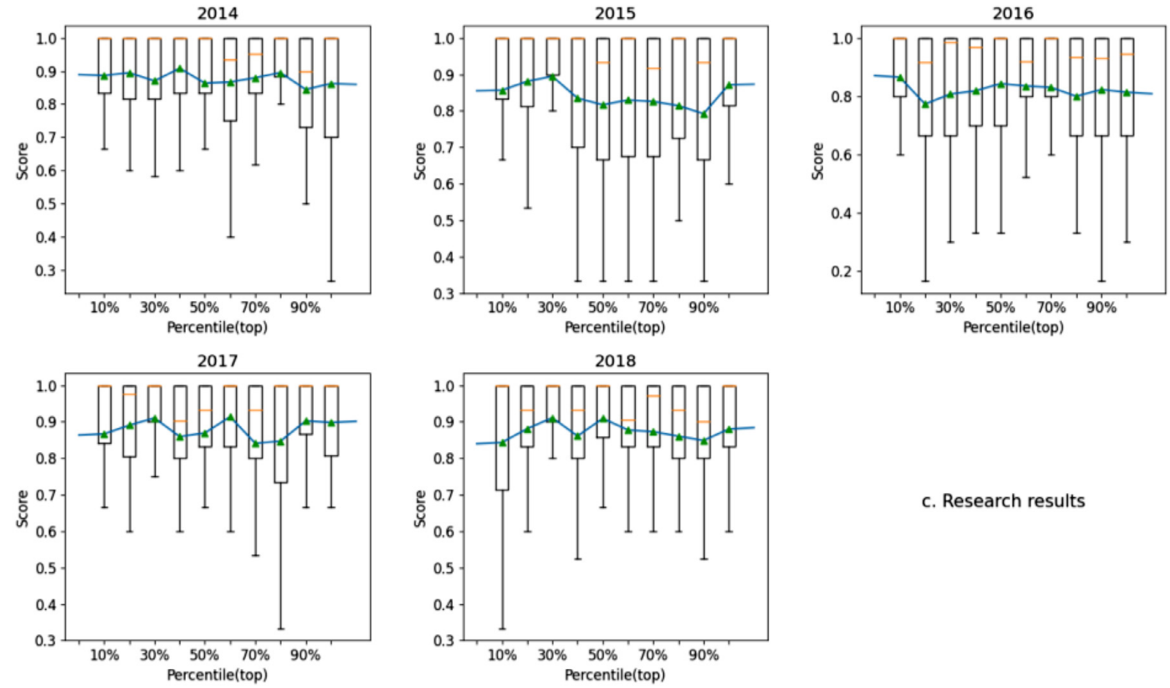


Fig. B7. The relationship between originality and knowledge combination. The X-axis represents the distribution of originality, from top 10% to bottom; the Y-axis represents the new combination score.



b. Research methods



c. Research results

Fig. B7. Continued

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