Scientometrics (2022) 127:6733–6761
https://doi.org/10.1007/s11192-022-04401-x

Measuring the interdisciplinarity of Information and Library Science interactions using citation analysis and semantic analysis

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Received: 14 August 2021 / Accepted: 4 May 2022 / Published online: 7 June 2022

Abstract

Interdisciplinary interaction and integration have become major features of current science and technology development. Hence, ways to measure the strength of the interdisciplinary interactions between two given disciplines has become a crucial issue. In this study, we propose a novel framework for measuring interdisciplinary interaction that is based on both citation analysis and semantic analysis. Within the framework, direct citations combined with bibliographic coupling reflect citation relationship of interdisciplinary knowledge, while an LDA model combined with a word embedding model are used to explore the integration and diffusion of knowledge via semantic similarity. The strength of the interdisciplinary interactions is then assessed with an entropy weighting method. A case study on the interactions between Information & Library Science and six other disciplines demonstrates the efficacy and reliability of the framework.

Keywords Interdisciplinary interactions · Citation analysis · Semantic analysis · LDA · Word2Vec

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Introduction

Interdisciplinary integration has become a major feature of modern science and technology (S&T) and a key source of innovation (Wang et al., 2016). As a case in point, the 2017 Nobel Prize in chemistry was awarded to physicists who solved a biology problem. According to the National Academies of Sciences Engineering and Medicine, interdisciplinarity is found in the cross combination of information, methods, techniques, tools, perspectives, concepts and/or theories from different disciplines or bodies of specialized knowledge. This integration enables us to advance our fundamental understanding of a phenomenon and to solve problems where the solutions are beyond the scope of a single discipline (Zhang et al., 2016). The importance of fostering interdisciplinarity has been increasingly recognized by both governments and S&T management institutions. Likewise, the scientific measurement of interdisciplinary interactions is considered to be a critical issue (Chi & Young, 2013).

Many studies have been devoted to measuring interdisciplinarity, through indicators like citation analysis (Bjorn, 2010) or co-word analysis (Deng et al., 2019). Citation analysis can trace the literature, helping to identify the learning and referring relationships between disciplines. For this reason, it has been widely applied as a tool for measuring interdisciplinary interactions. Leydesdorff and Ivanova (2020), for example, used direct citation and bibliographic coupling—forms of citation analysis—to reveal the process of knowledge transfer between disciplines. However, citation analysis can only reveal rough interdisciplinary relationships (Xu et al., 2017); it does not expose the results of knowledge transfer. There are also some studies emphasizing the importance of document content analysis, which can specifically reveal the evolution of interdisciplinary knowledge structure (Xu et al., 2017). For example, Xu et al. (2016) explored interdisciplinarity using co-word analysis. However, co-word analysis is not good at handling slight variations in terminology, such as the difference between "data mining" and "data analytics". For this reason, it can often fail to recognize the semantic relationships between terms from different disciplines (Wang et al., 2016).

Further, most studies on interdisciplinarity focus on the individual level—a single paper, a single journal, a single scholar, a single institution (Leydesdorff & Rafols, 2011; Mugabushaka et al., 2016; Rafols & Meyer, 2009; Xu et al., 2016), where the authors are inclined to investigate their own interdisciplinarity. However, with the increasing attention of countries on the top-level design and deployment of interdisciplinary work, quantifying the degree of interdisciplinarity between two specific disciplines has become something of great practical significance. Gauging interdisciplinarity helps us to better understand the overall problems of each discipline. Additionally, insights into the degree and strength of interactions between disciplines can help when optimizing the structure of S&T departments and in fostering top to bottom cooperation between different disciplines.

In this study, we propose a novel framework for measuring the strength of interdisciplinary interactions between two disciplines that is based on citation analysis and semantic analysis. The framework is designed to both trace the knowledge transfer process and gauge the effects of knowledge integration and diffusion. The overall model includes three indicators: direct citations, bibliographic coupling, and document content. Direct citations and bibliographic coupling inform the citation analysis, and an LDA model combined with a word embedding model creates a semantic solution for content similarity analysis. The discipline-keyword vectors generated by the embedding model are then used to detect the underlying semantics in large-scale tracts of text. Lastly, the strength of the interdisciplinary interactions is assessed with an entropy weighting method.

To demonstrate the reliability and feasibility of our method, we conducted a case study of the interdisciplinary interactions between “Information & Library science (LIS)” and six other disciplines—“Communication”, “Computer science, Information systems”, “Education & Educational Research”, “Geography”, “Social Sciences, Interdisciplinary”, and “Management”.

The rest of this paper is organized as follows. A brief review of relevant literature is presented in the next section. Then, the theoretical framework is introduced and explained, followed by the LIS case study. The last section summarizes the results, clarifies the implications and limitations, and provides suggestions for future research.

Related work

This section contains a brief review of the relevant literature in the areas of interdisciplinary interaction, citation analysis, topic models, word embedding, and mixed bibliometric methods.

Measuring interdisciplinary interactions

Woodworth was the first person to publicly use the term ‘‘interdisciplinary” in 1926, believing that it represented the integration of knowledge among different disciplines (Frank, 1988). With the increasing level of specialization in many fields over the past 20 years, interdisciplinary research has become more both more challenging and more necessary (Oliveira et al., 2018). As many researchers have found, solving research issues in one’s own field can often require paying attention to problems in another (Benito-Santos & Theron Sanchez, 2019). In the century that has passed since social scientists coined the term, many other terms have been derived in this vein—“interdisciplinary interactions”, “multidisciplinary”, and “transdisciplinary” to name a few. In our study, we follow the definition of the US National Academies (2005), considering interdisciplinary interactions as an evolutionary process of:

> integrating information, data, techniques, tools, perspectives, concepts, and/or theories from two or more disciplines or bodies of specialized knowledge to advance fundamental understanding or to solve problems whose solutions are beyond the scope of a single discipline or field of research practice.

Therefore, interdisciplinary interactions show two major features: knowledge transfer (Huang et al., 2019), and content relevance (Karunan et al., 2017; Xu et al., 2016).

Knowledge transfers, which can be represented by citation flows of papers and journals between disciplines, is the core characteristic of interdisciplinary interaction (Pierce, 2012). Citation analysis based on references of disciplines can: track knowledge flows (Rafols & Meyer, 2009); trace the interactions among authors’ roles in disciplines (Huang et al., 2021a); and reveal the academic writing processes in interdisciplinary settings (Gullbekk & Byström, 2019). In this way, mutual learning and the spread of knowledge can be demonstrated quite well.

Meanwhile, with the deepening of knowledge transfers and cognition fusion, the effect of interdisciplinary on different disciplines would be tested (Gullbekk & Byström, 2019). Some of the outlets for these effects include the use of consistent terms, or the expression of similar semantics, which can change if the influence of other disciplines takes hold (Rafols & Meyer, 2009; Xu et al., 2017). However, while citations in publications across disciplines can help to indicate whether interdisciplinary processes have taken place, they cannot explain or describe them (Gullbekk & Byström, 2019). To remedy such analytical one-sidedness, more and more researchers have begun to emphasize the similarity of content across different disciplines (Xu et al., 2016). Moreover, Zhou, Du, et al. (2019), Zhou, Huang, et al. (2019)) point out that combining bibliometric methods with advanced linguistic techniques is likely to result in better descriptions of exactly how an interaction is interdisciplinary.

In this study, our framework not only considers the process of interdisciplinary knowledge transfer (i.e., citation relationships) but also the ultimate effect that knowledge integration and diffusion has on a discipline (i.e., content relevance).

Citation analysis

Citation analysis, one of the most commonly employed methods to measure the degree of interdisciplinarity (Caroline et al., 2011), draws on the subject categories of citations to analyze interdisciplinary interactions (Deng & Xia, 2020). There are three main citation analysis methods: direct citation, co-citation, and bibliographic coupling. Direct citation is, arguably, the most widely used. It reflects a two-way interactive relationship and is the most direct form of knowledge exchange between two disciplines (Ma et al., 2019). Bibliographic coupling reflects the relationship between two disciplines that each cite another paper (Karunan et al., 2017). Co-citation is an inferred relationship between two cited papers based on the fact that they are cited together (Yang et al., 2019). Among these methods, bibliographic coupling and co-citation have strict duality in concept (Liu et al., 2021). Compared with co-citation, bibliographic coupling can be used to cluster recent papers but can rarely do so with very old papers (Boyack & Klavans, 2010). Thus, bibliographic coupling is more suitable for reflecting the *current* strength of interdisciplinary interactions between two disciplines (Ma et al., 2019).

A key aspect of citation analysis is the similarity index used to normalize the raw matrix within a given network (Adnani et al., 2020). The most widely-used indexes are the Jaccard index, Salton's Cosine, and Pearson's correlation. Of these, the Jaccard index (Jaccard, 1901) is a relatively robust measurement method that is often used to calculate the crossing degree or similarity between two different individuals or the difference between two differently-sized sets (Leydesdorff, 2008).

Topic models

Topic models are statistical models that cluster the latent semantic structure of documents via unsupervised learning. Since topic models consistently outperform the traditional cluster-based approach (Wei & Croft, 2006), they have been commonly used as a tool for content analysis (Nichols, 2014). The three used most often are latent semantic indexing (LSI) by Deerwester et al. (1990), the probabilistic latent semantic index (pLSI) by Hofmann (2017), and latent Dirichlet allocation (LDA) by Blei et al. (2003).

LDA is the most accepted topic modeling technique in bibliometrics (Heo et al., 2017). It is used to discover potential topics from vast tracts of document data with the results returned as a probability distribution of the topics found in each document. Compared to LSI, LDA has the advantage of explicitly modeling the latent topics. Compared to pLSI, LDA does not suffer as much from overfitting (Lu & Wolfram, 2012). Since LDA preserves the core statistical relationships in documents, these models are useful for basic tasks such as classification, novelty detection, summarization, relevance judgments, and similarity measurement (Blei et al., 2003). In the research of interdisciplinarity, an LDA model was notably used by Shang (2018), who unearthed potential topics and their composition to reveal the hottest interdisciplinary research topics. In this paper, we use LDA to calculate the probability distributions of keywords in the content of documents.

Word embedding

Word embedding is an application of deep learning from the field of natural language processing (NLP). It creates a way to detect underlying semantics in large-scale text by mapping words from vocabularies to vectors (Mikolov et al., 2013). Compared to other word embedding techniques, neural network algorithms are more effective at discovering word patterns with similar implications (Levy & Goldberg, 2014). The Word-2Vec method (Mikolov et al., 2013) is a paragon of neural network algorithms that can be used to detect a potential decomposition of a point-wise mutual information matrix (Levy & Goldberg, 2014). Word2Vec consists of two models: a Skip-Gram model and a continuous bag-of-words model (CBOW). The CBOW model predicts a word from context, i.e., based on the surrounding words, while the Skip-Gram model predicts the context from a given word (Zhang et al., 2018). Compared to CBOW, Skip-Gram has proved to have a tiny advantage with bibliometric data (Hu et al., 2018; Zhang et al., 2018).

Mixed bibliometric methods

In recent years, many studies have relied on mixed bibliometric methods. This may be because the combination of citation analysis and text analytics can more precisely identify and measure knowledge flows (Kim et al., 2018). Using mixed methods also tends to reduce dependencies on the meta data of publications, such as subject categories. More importantly, it provides better adaptability to big data (Kim & Oh, 2018). As such, mixed methods have found their way into many applications including topic analysis (Loureiro et al., 2020), citation recommendation (Dai et al., 2019), and emerging trend identification (Ayele et al., 2019).

There have also been some studies related to interdisciplinarity that have exploited mixed methods. However, these mostly focusing on the interdisciplinary nature of a single object (Benito-Santos & Theron Sanchez, 2019; Ozkaya, 2020; Langer et al., 2021), i.e., a paper, an author, a journal, a scholar, an institution. For example, Raimbault (2019) coupled citation analysis with text-mining techniques to map interdisciplinary landscapes in the field of geography. Chen et al. (2019) conducted an in-depth evaluation of health information systems (IS) research published in IS journals by combining citation analysis,

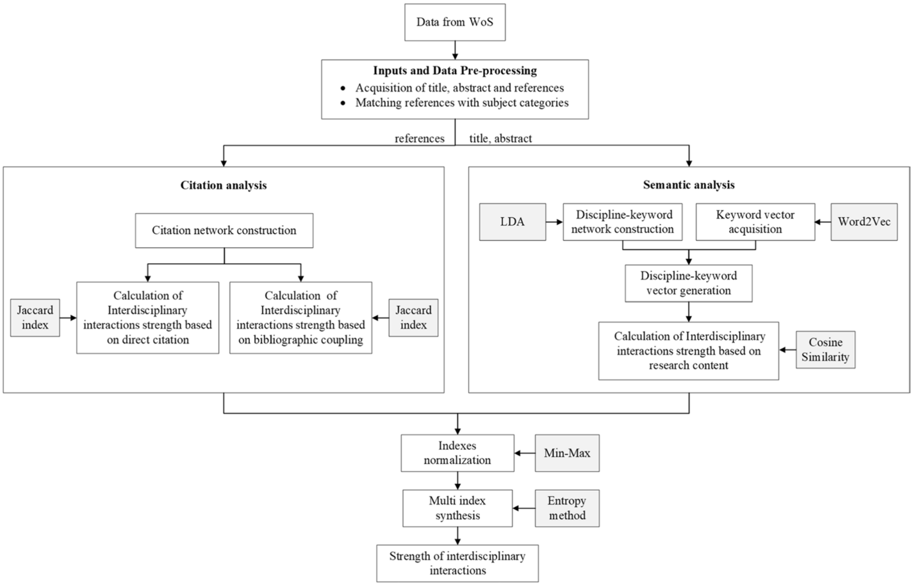

Fig. 1 Our framework for measuring interdisciplinary interactions

semantic analysis, and social network analysis. In the research of Lee et al. (2019), citation network analysis integrated with topic model was used to help identify those cited papers that cut across domains. Further, citation networks combined with text mining have been used to identify the evolutionary pathways of multiple disciplines (Zhou et al., 2018). In the study of Yu et al. (2017), the interdisciplinary nature of intuitionistic fuzzy sets was revealed by text mining and citation analysis.

Mixed methods have not been directly used in the measurement modeling of interdisciplinary interactions between two disciplines. Rather, interdisciplinarity has been regarded as either an insight into some experimental results, or a byproduct of text mining, or as a way to understand a topic evolution process (Chen et al., 2019; Xu et al., 2019). More importantly, existing mixed methods tend to analyze the similarity of text from the perspective of co-words. However, traditional keyword analysis tends to ignore contextual semantic relations (Hu et al., 2018; Onan, 2019), which means it cannot truly gauge the effects of knowledge integration and diffusion.

In our study, we propose a novel framework for measuring the strength of interdisciplinary interactions between disciplines, with a particular emphasis on semantic solutions for detecting the underlying semantics in large-scale tracts of text.

Methodology

Our framework for measuring interdisciplinary interactions is shown in Fig. 1. As the figure shows, a citation network is constructed and analyzed to reveal mutual learnings and knowledge transfers between two given disciplines. LDA and Word2Vec combine to explore the relevance of the document content and to investigate the effect of knowledge integration and diffusion between the disciplines.

Inputs and data pre-processing

The most important thing to note about our framework is that it finds the interdisciplinary interactions between two specific disciplines, noted as Discipline X and Discipline Y. Thus, as inputs to the model, we acquired the titles, abstracts and references of academic papers for each discipline we were interested in examining from the Web of Science (WoS). Each reference was then assigned a discipline corresponding to the subject categories of WoS using Python. Key terms were retrieved from the titles and abstracts of the papers using an NLP technique. This technique also included a term clumping model to remove noise, consolidate terms, and identify core terms (Zhang et al., 2014).

Citation analysis

Our citation analysis depended on both direct citations and bibliographic coupling, with the Jaccard index used as the similarity metric. The higher the value, the stronger the interdisciplinary interaction. We chose the Jaccard index because it is simpler and more effective than several other traditional similarity metrics, e.g., Euclidean or Manhattan (Le & Phuong, 2020). Additionally, it satisfies the "identity property" or "triangle property" of a metric (Carass et al., 2020) unlike other metrics such as DICE. Lastly, it places focus on the strong links in a data set (Leydesdorff, 2008).

Constructing the citation network

The first step in constructing a citation network is to construct a citation matrix of papers and their references $[C]$, represented as:

$$[C] = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1j} \\ c_{21} & c_{22} & \cdots & c_{2j} \\ \cdots & \cdots & \cdots & \cdots \\ c_{i1} & c_{i2} & \cdots & c_{ij} \end{bmatrix}, \tag{1}$$

where the element c_{ij} equals 1 if paper i cites reference j, and 0 otherwise. We further use c_{ij} to calculate the citation frequency of papers between disciplines w_{xy}, computed as:

$$w_{xy} = \sum_{i \in D_x, j \in D_y} c_{ij} \tag{2}$$

where $i \in D_x$ represents papers belonging to Discipline X, and $j \in D_y$ represents papers belonging to Discipline Y.

The second step of this stage is to construct a discipline-citation matrix $[W]$, represented as:

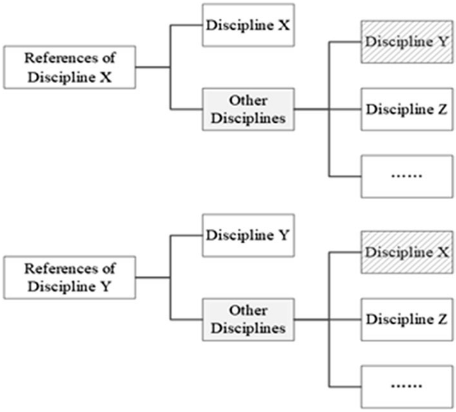

Fig. 2 Direct citation relationship between Discipline X and Discipline Y

$$[W] = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1m} \\ w_{21} & w_{22} & \cdots & w_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ w_{m1} & w_{m2} & \cdots & w_{mm} \end{bmatrix}, \tag{3}$$

where the element w_{xy} is the number of times that Discipline X cites papers from Discipline Y.

The last step is to generate a discipline-citation network, where the nodes represent disciplines, and there is an undirected edge between two nodes if they have a citation relationship. The weights of the edges are represented by w_{ij}.

Calculating the strength of interdisciplinary interactions based on direct citations

Figure 2 shows the structure of direct references for Discipline X and Discipline Y.Here, II_{xy}^{dc} denotes the strength of interdisciplinary interactions between Discipline X and Discipline Y based on direct citations. The direct citations between Disciplines X and Y fall into two groups: the references Discipline X makes to Discipline Y, and the references of Discipline Y makes to Discipline X. These are marked as boxes shaded with diagonal lines in Fig. 2. Following Jaccard's calculation formula, the numerator is the intersection of these two groups, which is the minimum number of references shared by the two sets. The denominator is the sum of the references made to all other disciplines (the shaded boxes) minus the numerator. Therefore, II_{xy}^{dc} can be represented as:

$$II_{xy}^{dc} = \frac{\min\left\{w_{xy}, w_{yx}\right\}}{w_{x'} + w_{y'} - \min\left\{w_{xy}, w_{yx}\right\}} \tag{4}$$

where w_{xy} is the number of references of Discipline X made to Discipline Y, w_{yx} is the number of references of Discipline Y made to Discipline X, $w_{x'}$ represents the number of references of Discipline X made to disciplines other than Discipline X, $w_{y'}$ represents the number of references of Discipline Y made to disciplines other than Discipline Y.

Calculating the strength of interdisciplinary interactions based on bibliographic coupling

The bibliographic couplings between Discipline X and Discipline Y mainly focus on common references. Here, II_{xy}^{bc} denotes the strength of interdisciplinary interactions between Discipline X and Discipline Y based on bibliographic couplings. Following Jaccard's calculation formula, II_{xy}^{bc} can be computed as follows:

$$II_{xy}^{bc} = \frac{o_{xy}}{q_x + q_y - o_{xy}} \tag{5}$$

where o_{xy} represents the number of all common references between Discipline X and Discipline Y. q_x and q_y are the reference counts for Discipline X and Discipline Y, respectively.

Semantic analysis

The purpose of the semantic analysis is to measure the strength of the interdisciplinary interactions between two disciplines by exploring the semantic relationships reflected in keywords (Wang et al., 2013).

Constructing the discipline-keyword network

The first step in constructing the discipline-keyword network is to use LDA to obtain the keyword distributions for both Discipline X and Discipline Y. To ensure the accuracy of the LDA model, we calculated the perplexity of the corpus to help decide the number of topics (Blei et al., 2003). Perplexity is formulated as:

$$\text{Perplexity }(D) = \exp\left\{-\frac{\sum_{d=1}^{M}\log p\left(w_d\right)}{\sum_{d=1}^{M} N_d}\right\} \tag{6}$$

where D is the test set in the corpus, w_d represents the words in document d, and $p\left(w_d\right)$ is the probability of w_d. In addition, N_d and M serve as the total number of words in document d and the total number of words, respectively.

We chose to synthesize the keywords through the LDA model as opposed to just taking the author keywords because using so few keywords may lead to data sparsity (Benito-Santos & Theron Sanchez, 2019). Also, it has been well documented that author-chosen keywords lack rigor and can be undiscriminating as far as disciplinary attributes are concerned (Lu et al., 2019). Either issue would mean we failed to derive a comprehensive representation of the given disciplines. Thus, we synthesized the keywords, generated by cleaning the titles and abstracts of the papers in Discipline X and Discipline Y. Through the LDA model, the concepts referred to in a document are represented as a topic probability distribution, and each topic is represented as a keyword probability distribution.

Multiplying the discipline-topic matrix with the topic-keyword matrix results in a discipline-keyword matrix [A], represented as:

$$[A] = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1p} \\ a_{21} & a_{22} & \cdots & a_{2p} \\ \cdots & \cdots & \cdots & \cdots \\ a_{m1} & a_{m2} & \cdots & a_{mp} \end{bmatrix}, \tag{7}$$

where the element a_{mp} is the probability distribution of Discipline m for keyword p.

Generating the keyword vector

Word2Vec is used to generate the keyword vectors. Its training procedure is as follows. First, the word sequences generated from the text in the abstracts and titles are input into the Word2Vec model to be trained as a corpus, and then the Skip-Gram model is used to train the corpus. Finally, through a well-trained Word2Vec model, all the keywords are mapped as vectors originating from a point in a multi-dimensional semantic space.

Calculating the strength of interdisciplinary interactions based on document content

After obtaining the discipline-keyword network and the keyword vectors, the next step is to calculate the strength of the interdisciplinary interactions based on document content. First, the content of the documents is converted into a vector representation by loading the keyword vectors into A(m, p). Here, V_{mp} denotes a discipline-keyword vector, calculated as:

$$V_{mp} = \sum A(m, p) * V_p \tag{8}$$

where V_p denotes the vector of keyword p.

Then, the similarity between discipline-keyword vectors of disciplines is calculated according to the cosine similarity. Cosine similarity is one of the most popular similarity measures employed in NLP and can represent cognitive similarity beyond simple linguistic similarity (Benito-Santos & Theron Sanchez, 2019). Further, cosine similarity has been successfully applied in many applications (Ke, 2019), including text documents clustering (Guo et al., 2020), information retrieval (Hu et al., 2021), and data mining (Ali et al., 2020). Also, the cosine metric remains one of the best measures for visualizing vector space (Leydesdorff, 2008). II^{rc}_{xy} denotes the strength of the interdisciplinary interactions between Discipline X and Discipline Y based on the document content, formulated as:

$$II^{rc}_{xy} = COS(X, Y) \tag{9}$$

where COS(X, Y) is the cosine distance between the vector of Discipline X and Discipline Y.

Multi-index synthesis

The framework measures the strength of the interdisciplinary interactions between disciplines comprehensively using three indicators—II^{dc}_{xy}, II^{bc}_{xy}, II^{rc}_{xy}.

Note that each indicator is standardized with Min–Max Normalization (Isler & Kuntalp, 2010), and calculated as follows:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{10}$$

where x is the original value, and x' is the normalized value.

To integrate these three indicators, we must weight each one. There are two ways to determine the appropriate weight: subjective weight and objective weight. We opted for the objective weighting method because it can overcome the randomness of subjective weighting, and more objectively represents the importance of the weight. Further, from a comparison of the various objective weighting methods, we decided to use the entropy weighting method for our calculations.

The entropy weighting method is an objective method for determining the index weight based on mathematical statistics and the basic principle of information theory (Wang & Li, 2021). It effectively considers the degree of variation in the indicators used to measure the strength of the interdisciplinary interactions. In this paper, the entropy weight of each index is defined as W_β. The calculation method is shown in Formulas (11), (12) and (13).

$$f_{\alpha\beta} = \frac{q_{\alpha\beta}}{\sum_\alpha q_{\alpha\beta}} \tag{11}$$

where $f_{\alpha\beta}$ denotes the standardized value of the βth index in the αth sample, and $q_{\alpha\beta}$ is the value of each indicator.

$$E_\beta = \frac{\sum_\alpha f_{\alpha\beta} \ln\left(f_{\alpha\beta}\right)}{\ln(N)} \tag{12}$$

where E_β of the βth index is the information entropy, and the range of the entropy value E_β is [0,1]. N is the number of indicators. If the information entropy of an index is smaller, it means that the variation degree of the index value is greater, more information is covered, and it has a greater ability to influence the overall evaluation. Hence, higher weight should be given to the index. The final weight calculation is then formulated as:

$$W_\beta = \frac{1-E_\beta}{M-\sum_\beta E_\beta} \tag{13}$$

Last, the comprehensive strength of interdisciplinary interactions between Discipline X and Discipline Y is calculated as:

$$II_{xy} = W1 * II_{xy}^{dc} + W_2 II_{xy}^{bc} + W_3 II_{xy}^{rc} \tag{14}$$

where W_1, W_2, W_3 are the weights of the three indicators calculated by the entropy weight method (Wang & Li, 2021).

Empirical study

We chose LIS as the major discipline, i.e., Discipline X, for our case study since LIS combines basic research, like mathematics, computer science, and physics, with the real-world needs of social sciences. We further chose to pair LIS with six different Discipline Ys through the framework to show its efficacy with a range of different study areas—some with clear interdisciplinary ties to LIS, others without such obvious correlations. The six selected disciplines were "Education & Educational research", "Computer science, Information systems", "Management", "Geography", "Communication", and "Social Sciences, Interdisciplinary". It is worth reiterating that the framework can be used to examine any two disciplines. However, considering a reasonable data volume and processing time, we

Table 1 Number of papers and references of seven disciplines

Subject category	Papers	References
Information Science & Library Science (LIS)	4417	75,915
Communication	5243	369,168
Computer Science, Information Systems	35,281	369,217
Education & Educational Research	15,438	167,803
Geography	5823	99,128
Social Sciences, Interdisciplinary	7152	121,600
Management	13,897	231,297

Table 2 Data cleaning results (partial)

Number	Keyword	Frequency
1	Social medium	1511
2	Communication	363
3	Climate change	278
4	Relationship satisfaction	211
5	Social network	176
…	…	…
4180	Image appeal	3

felt six examples were enough to showcase the depth and breadth of the framework. We had three major criteria for selecting the disciplines.

(1) First, we were inclined toward disciplines with ties to LIS on an intuitive level. Choosing these disciplines would help us to conduct our validation tests. LIS is a typical interdisciplinary field that has been spearheading cross-disciplinary research (Holland & George, 2008). As such, it connects multiple studies with real-world needs discussed in areas like mathematics and computer science, the social sciences, and the management sciences (Huang et al., 2021b). On these grounds, we selected "Computer Science", "Social Science" and "Management".

(2) Second, a discipline has to reach a certain level of maturity before it can support communication and cross-overs into other disciplines. According to the research of Karunan et al. (2017), if too few papers have been written on discipline, interdisciplinary interactions do not have a chance to develop and, if they do, they may not yet have developed strongly. Additionally, we wanted to test the framework's ability to cope with large-scale data. Hence, with a view on the past five years, we further selected subcategories of two disciplines selected under Criteria 1 with the largest number of papers. Among the seven subcategories of Computer Science listed by WoS, we chose "Computer Science, Information Systems". Similarly, we chose "Social Sciences, Interdisciplinary" for "Social Science", even though "Social Sciences, Mathematical Methods" seemed to be more related to LIS.

Table 3 The abbreviation–full journal title–Subject category comparison table (partial)

The abbreviation	Full journal title	Subject category
Int J Inform Manage	International Journal of Information Management	Information Science & Library Science
Commun Methods Meas	Communication Methods and Measures	Communication
Comput Netw	Computer Networks	Computer Science, Information Systems
Educ Psychol	Educational Psychologist	Education & Educational Research
Dialogues Hum Geogr	Dialogues in Human Geography	Geography
Soc Sci Comput Rev	Social Science Computer Review	Social Sciences, Interdisciplinary
…	…	…
Acad Manag Ann	Academy of Management Annals	Management

Table 4 Discipline citation matrix

	LIS	Comms	IS	Edu	Geo	Soc	Mgmt
Information & Library Science (LIS)	34,210	5372	16,297	2673	1882	3070	27,446
Communication (Comms)	4644	45,130	1212	1903	1064	4750	5701
Computer Science, Information Systems (IS)	18,105	2230	138,505	2032	2316	1447	20,321
Education & Educational Research (Edu)	3611	3183	1641	152,921	2289	6233	10,959
Geography (Geo)	1711	955	1845	2268	56,733	3259	5081
Social Science-Interdisciplinary (Soc)	2959	4791	911	5085	3544	24,835	10,978
Management (Mgmt)	15,102	5578	10,879	4893	4390	8875	286,253

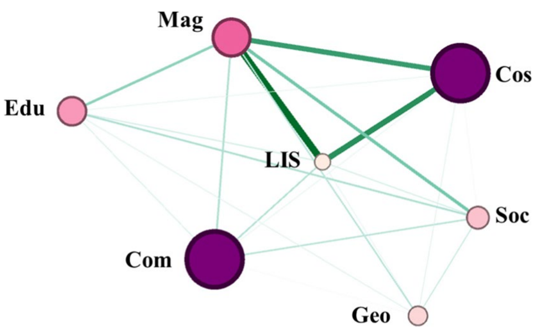

Fig. 3 Citation network of disciplines

(3) Third, we paid attention to the diversity, wanting to test the framework across a broad spectrum of disciplines. On these grounds, we added "Communication", "Education & Educational research" and "Geography".

Table 5 Citation analysis of the six disciplines to LIS

Subject category	Direct citation	Bibliographic couplings
Communication	4644	13,525
Computer Science, Information Systems	16,297	36,277
Education & Educational Research	2673	10,887
Geography	1711	7929
Social Science, Interdisciplinary	2959	16,532
Management	15,102	32,269

Table 6 Strength of the interdisciplinary interactions between six disciplines and LIS

Subject category	Based on direct citations (%)	Based on bibliographic coupling (%)
Communication	4.301	8.923
Computer Science, Information Systems	4.542	8.461
Education & Educational Research	1.612	4.453
Geography	1.270	4.517
Social Science, Interdisciplinary	1.793	8.662
Management	7.449	11.119

More specifically, "Communication" is an applied and theoretical discipline, "Computer Science, Information Systems" and "Education & Educational research" are both applied disciplines, "Geography" is a natural discipline, and "Social Science, Interdisciplinary" and "Management" are both comprehensive disciplines. In a word, we suppose that the six disciplines we selected for comparison with LIS represent a comprehensive cross-section of disciplines.

Data collection and pre-processing

The search strategy for retrieving the papers and references in each of the seven disciplines included "WC = Information Science & Library Science", "WC = Communication", "WC = Computer Science, Information Systems", "WC = Education & Educational Research", "WC = Geography", "WC = Social Sciences, Interdisciplinary", "WC = Management". We searched SCI-EXPANDED and SSCI for articles in English over the period 2010 to 2019 and retrieved 87,251 papers and 1,434,128 references as shown in Table 1. Note that the cited data were generated based on citations from all disciplines, not merely just the seven disciplines.

Here, when a journal had been assigned to multiple WCs, we assigned it to each WC. Then, when downloading the articles, we only chose journals from SCI and SSCI. We also

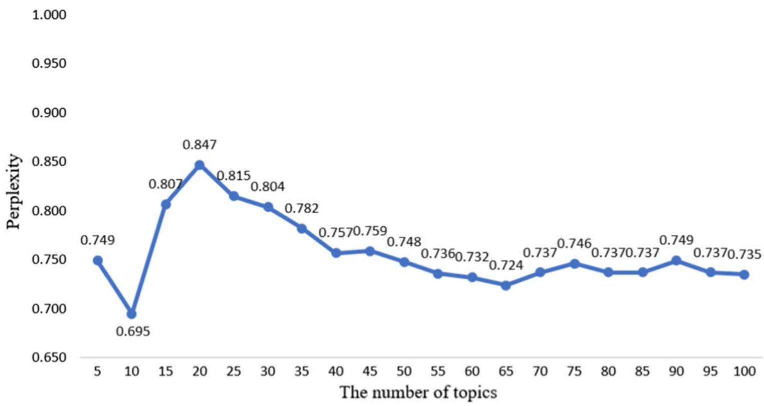

Fig. 4 Perplexity change curve

Table 7 Discipline-keyword network (Partial)

Subject category	Keyword distribution
Information & Library Science	"social-media": 0.04, "libraries": 0.018, "big data": 0.017, "behavior": 0.014, "health practitioners": 0.013, "social commerce": 0.012, ……
Communication	"social media": 0.05, "fake news": 0.014, "tweets": 0.013, "news media": 0.012, "conflict": 0.012, "mental illness": 0.012, ……
Computer Science, Information Systems	"algorithm": 0.176, "performance": 0.013, "reliability": 0.011, "accuracy": 0.009, "deep learning": 0.007, "applications": 0.006, ……
Education & Educational Research	"universities": 0.023, "academic performance": 0.016, "feedback": 0.014, "self-efficacy": 0.014, "international students": 0.013, "teacher education": 0.011, ……
Geography	"migration": 0.031, "geography": 0.026, "climate change": 0.016, "public-space": 0.013, "citizenship": 0.011, "transport": 0.008, ……
Social Science-Interdisciplinary	"happiness": 0.026, "life satisfaction": 0.025, "disabilities": 0.018, "subjective well-being": 0.013, "marriage": 0.011, ……
Management	"job-satisfaction": 0.029, "resources": 0.016, "firm performance": 0.014, "abusive supervision": 0.013, "sustainability": 0.012, ……

removed all references excluded from the SCI and SSCI databases, and we removed duplicate references. The number in Table 1 is the number of references after filtering.

The NLP and term clumping function within ITGInsight[1] was applied to retrieve and clean keywords from the titles and abstracts of papers. Following Wang et al. (2021), meaningless words were removed according to the list of stop words; then, the title and abstract were merged to extract the keywords. Irrelevant keywords were removed manually leaving a total of 4180 valid keywords (Table 2).

[1] ITGInsight is a text mining and visualization software for bibliometric data, such as scientific papers, patents, reports and newspapers. Please visit the website for details: http://cn.itginsight.com.

Table 8 Keyword vectors (partial)

Keyword	Keyword vector
Protocol	[– 0.2624, – 0.1043, 0.5251, – 0.1086, 0.7158, – 0.2288, …]
Social medium	[– 0.8498, 1.3760, – 0.7888, 0.3469, – 0.6862, – 0.6375, …]
Energy consumption	[– 0.5506, 0.1487, 0.3965, – 0.6347, 0.5142, – 0.3295, …]
Big data	[– 0.4847, 0.6796, 0.2859, – 0.3489, – 0.2411, – 0.2434, …]
Social network	[– 0.3273, 0.6461, 0.6722, – 0.3651, 0.0635, – 0.1393, …]
Energy efficiency	[– 0.3726, 0.0966, 0.0613, 0.0577, 0.4531, – 0.2191, …]

Table 9 Strength of interdisciplinary interactions between six disciplines and LIS

Subject category	Based on document content (%)
Communication	19.848
Computer Science, Information Systems	28.330
Education & Educational Research	27.003
Geography	16.577
Social Science-Interdisciplinary	26.006
Management	25.832

Table 10 The comprehensive strength of interdisciplinary interactions between six disciplines and LIS

Subject category	Based on direct citation (%)	Based on bibliographic coupling (%)	Based on document content (%)	Final results (%)
Communication	4.301	8.923	19.848	10.490
Computer Science, Information Systems	4.542	8.461	28.330	12.972
Education & Educational Research	1.612	4.453	27.003	10.167
Geography	1.270	4.517	16.577	6.934
Social Science-Interdisciplinary	1.793	8.662	26.006	11.324
Management	7.449	11.119	25.832	14.175

After downloading the articles provided by Journal Citation Reporters (JCR), we used Python to match all abbreviations and journal names according to the ESI journal list. This resulted in 12,186 journals and 252 journal-subject category mappings. Partial results are shown in Table 3.

Measuring interdisciplinary interactions based on citation analysis

We next constructed the discipline citation matrix, as shown in Table 4.

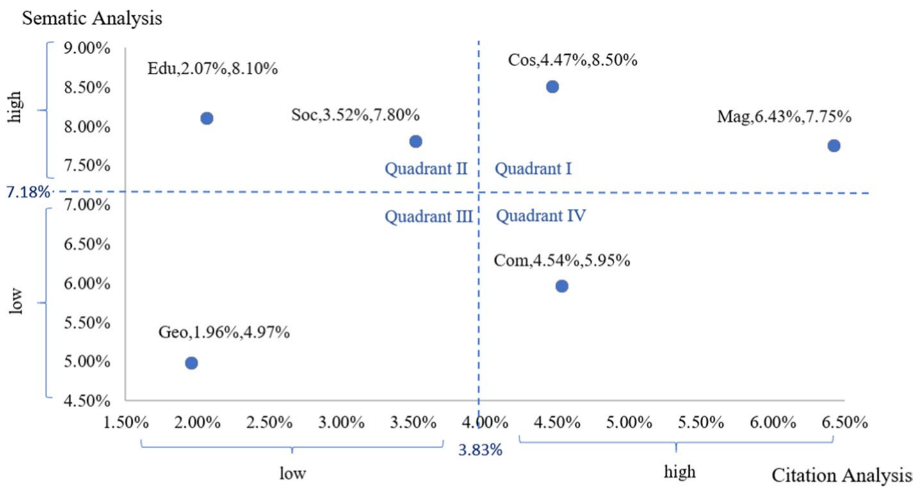

Fig. 5 Distribution of interdisciplinary interactions

This matrix was then imported into Gephi[2] to visually display the citation relationships among disciplines, as shown in Fig. 3. The size of each node relates to the total number of references for that discipline, and the thickness of the edges represents the number of citations between those disciplines.

From the illustration, we can see that LIS has a closer relationship to Management and Computer Science, Information Systems than to the other disciplines (hereafter simply Information Systems). By contrast, LIS is relatively distant to Geography and Education & Educational Research (hereafter Education), which means that knowledge transfer and academic exchanges between the two fields are poor.

The direct citations and bibliographic couplings of the six disciplines to LIS are shown in Table 5, while Table 6 shows the strength of interdisciplinary interactions based on both direct citation and bibliographic coupling.

Measuring interdisciplinary interactions based on document content

Following the design in section "Semantic analysis", LDA was first used to generate a discipline-keyword matrix for each discipline. Following Cao et al. (2009), the number of topics was determined by perplexity. More specifically, we set the variation range of the number of topics to [0,100] and set the step size to 5. Then, we plotted the perplexity curve against the number of topics, as shown in Fig. 4.

Figure 4 depicts that the degree of confusion reaches its lowest value of 0.695 with 10 topics. We therefore specified 10 topics per discipline, with each topic represented by its top 10 keywords.

[2] https://gephi.org/.

From the 7 disciplines and 4180 keywords, corresponding discipline-topic matrices and topic-keyword matrices were constructed then multiplied into a discipline-keyword matrix for each pair. The results are shown in Table 7. The value after each keyword represents the probability of a certain keyword appearing in this discipline.

Next, the Word2Vec model was applied to map keywords into dense word vectors to capture semantic information. Since higher dimensions have been shown to capture better semantics (Wang et al., 2015), we set the number of dimensions for the vectors to 450 and turned the keywords of 7 disciplines into semantic-level vectors with the trained model. A small sample of the keyword vectors is given in Table 8.

Calculating the cosine similarity as per Formula (6), we generated the strength of the interdisciplinary interactions between LIS and the other six disciplines. The results are shown in Table 9.

Results analysis

Min–max normalization was used to standardize our three interaction indicators, and the entropy method was used to calculate the weight of each index. The strength of the interdisciplinary interactions between LIS and the six disciplines is shown in Table 10.

There are some observations based on above analysis results:

(1) The strength of the interdisciplinary interactions between LIS and the six disciplines range between 6.934 and 14.175%, which indicates that our methods can indeed measure and rank the interdisciplinary interactions between disciplines. At the same time, we can also conclude that LIS is interdisciplinary, because it has a certain degree of intersection with other disciplines.
(2) The most interdisciplinary interactions occur between LIS and Information Systems and LIS and Management. Lin et al. (2017) prove that the speed of knowledge diffusion between LIS and Management continues to accelerate, while Shi (2018) state that both LIS and Information Systems involve information science, especially when it comes to system design, technology research, and algorithm optimization.
(3) The strength of the interdisciplinary interactions between LIS and Geography is very low. Geography is a specialist discipline, so it may be difficult for knowledge to flow from LIS to geography. An example of the crossover is the use information technology from LIS, such as data mining, to solve environmental problems (Huang & Ying, 2020).

Since citation analysis and semantic analysis reflect the knowledge transfer process and the effects of integrating interdisciplinary, respectively, we combined the index values of direct citation and bibliographic coupling for further analysis. First, the results of citation analysis and semantic analysis were divided into two levels “low cross degree” and “high cross degree” according to their average, and the four quadrants were divided. The map is shown in Fig. 5.

From Fig. 5, we observe:

(1) The relationship between the two ways of measuring interdisciplinary interactions—i.e., citation analysis and semantic analysis—is positive. This indicates that the strength of the knowledge integration and the diffusion effects (the relevance of the content) depends on the quality of the knowledge transfer process (the citations).

Table 11 Four baselines

Index	Formula	Description
Rao-Stirling coefficient	$Rao-stirling = \sum_{i,j} p_i p_j d_{i,j}$	p_i, p_j are the percentages of references for disciplines i and j respectively; $d_{i,j}$ is the distance between the two disciplines in a discipline citation network
Salton coefficient	$S = \frac{o_{xy}}{\sqrt{q_x} \times \sqrt{q_y}}$	S is the Salton coefficient value between two disciplines; o_{xy} is the number of common references of Discipline X and Discipline Y; q_x, q_y are the number of references given by Discipline x and Discipline y
Overlap degree	$N_{xy} = \frac{o_{xy}}{\sqrt{N_x N_y}}$	N_x, N_y are the number of papers in Discipline X and Discipline Y; o_{xy} is the number of papers shared by Discipline X and Discipline Y
ID value	$ID = \frac{1}{\sum_{i \neq j} p_i p_j (1 - d_{i,j})}$	$d_{i,j}$ is the distance between two disciplines in the discipline citation network

Table 12 Comparison of the results between our method and mainstream indicators

	Comms		IS		Edu		Geo		Soc		Mgmt	
	Value	#Rank	Value	#Rank	Value	#Rank	Value	#Rank	Value	#Rank	Value	#Rank
Standard (Result from experts)	**–**	**#4**	**–**	**#1**	**–**	**#5**	**–**	**#6**	**–**	**#3**	**–**	**#2**
Our method	10.490	#4	12.972	#2	10.167	#5	6.934	#6	11.324	#3	14.175	#1
Salton	8.079	#6	21.668	#2	9.646	#4	9.140	#5	17.207	#3	24.352	#1
Rao-Stirling	0.050	#4	0.369	#1	0.061	#3	0.031	#6	0.143	#2	0.046	#5
Overlap degree	3.115	#5	10.340	#1	0.230	#6	4.967	#4	5.658	#3	7.454	#2
ID	2007	#4	271	#1	1650	#3	3211	#6	699	#2	2181	#5

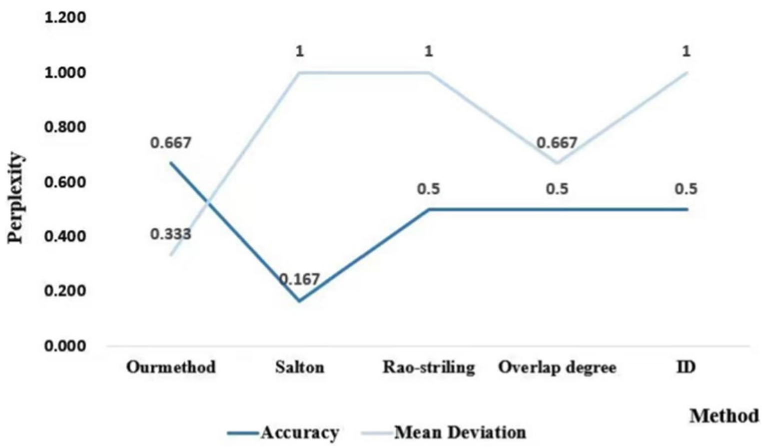

Fig. 6 Comparison of accuracy and mean deviation

(2) However, we also see exceptions. Although LIS and Education appear to have weak interdisciplinary interactions based on citation analysis, the interactions are much stronger when based on semantic analysis (Quadrant II). This is mainly because many countries have policies that actively promote interactions between these two disciplines. Although there are few citation relationships between LIS and Education, the relatively high semantic similarity between these two disciplines indicates their potential for greater interdisciplinarity. For this reason, we predict that the number of cooperative projects and studies between these two disciplines will increase in the future.

(3) In Quadrants I and IV, the interactions between LIS and Communication, LIS and Management and LIS and Information Systems are all strong when looking the scores for citation analysis. However, there are great differences when we look at the semantic analysis scale. Compared to a single measurement method based on citations alone, our method also reflects interdisciplinarity at a content and cognitive level, offering, at the least, a more comprehensive set of measurement results.

Validation

Evaluation with other methods

To validate the effectiveness of our framework, we convened an expert panel and also compared our results to four mainstream indexes of interdisciplinarity.

The four indexes compared were the Salton coefficient (Salton & McGill, 1986), the Rao-Stirling coefficient (Stirling, 2007), overlap degree (Pan et al., 2013), and ID value (Zhang et al., 2016). Details of the formulas used to calculate each of these indexes are given in Table 11.

First, we invited 30 experts to conduct a questionnaire on preference ordering. They came from multiple disciplines including LIS, management science, computer science and social science—generally, the seven disciplines we selected for the case study. The institutions represented include the University of Leuven in Belgium, the Georgia Institute of Technology in the United States, the science and technology research center of Leiden

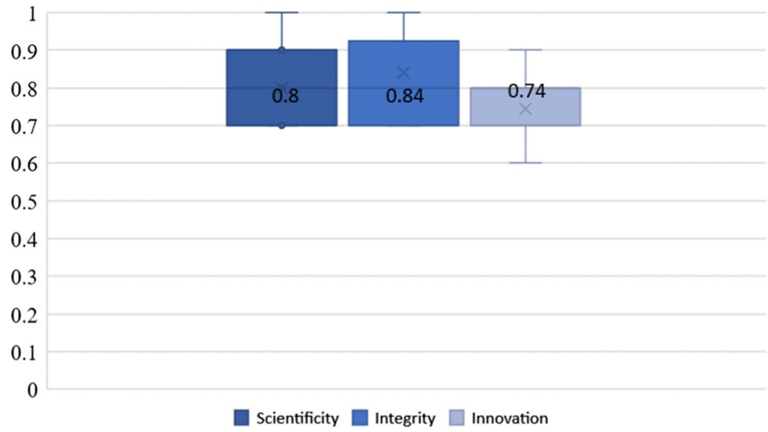

Fig. 7 Results of expert evaluation

University in the Netherlands, and the University of Technology Sydney. Every expert was asked to rank the interdisciplinary interactions between the six selected disciplines and LIS, and their results can be thought of as a validation standard. We then calculated the strength of the interdisciplinary interactions between LIS and the six disciplines by using the four indices and ranked the results. The details are provided in Table 12. The first line presents the rank of interdisciplinary interactions between LIS and six disciplines generated by 30 experts, which is in bold and regarded as the standard for comparing the proposed method and four mainstream indexes.

The performance of the proposed model was evaluated in comparison with other mainstream methods in terms of Accuracy (*Acc*) (Formula 15) and mean deviation (*Mean dev*) (Formula 16): the higher the accuracy, the higher the calculation accuracy of the method; the smaller the mean deviation, the higher the calculation stability of the method. The comparison result is shown in Fig. 6.

$$\text{Accuracy} = \frac{RR'}{r} \tag{15}$$

where RR' is the same number of the interaction strength ranking obtained in this study and interaction strength ranking determined by the experts.r is the number of rankings.

$$\text{Mean Deviation} = \frac{\sum |R_i - R_i'|}{r} \tag{16}$$

where R_i is the interaction strength ranking obtained in this study, R_i' is the interaction strength ranking determined by the experts.

From Table 11 and Fig. 6, we can see that:

(1) Our method had the highest *Acc* (0.667) and the smallest *Mean dev* (0.333). Salton's accuracy was only 0.167 and the mean deviation of the overlap degree and ID value reached 0.667 and 1 respectively. This means our method was significantly more accurate and stable than the other four methods in measuring the strength of interdisciplinary interactions. From this, we conclude that our framework is realistic, distinguishable, and performs well.

(2) It is notable that the Rao-Stirling coefficient and the ID value both arrived at the same result (*Acc* 0.5 and *Mean dev* 1). Both are based solely on citation networks. The *Acc* and *Mean dev* of these two indexes were both inferior to our methods, indicating the comprehensiveness and generality of our framework. This suggests that integrating citation analysis and semantic analysis to measure the strength of interdisciplinary interactions is highly beneficial.
(3) Another noteworthy result is that the overlap degree yielded the best accuracy of the four baselines. Overlap degree is an interdisciplinary index that measures the interdisciplinary interactions between two disciplines from the perspective of common articles in both disciplines. Another form of interdisciplinary interaction is through papers that appear commonly in each of two disciplines (Karunan et al., 2017). Our results suggest that the number of common articles between two disciplines can reflect the intersections of the two disciplines, at least to a certain extent.

Expert evaluation

As mentioned, the method was evaluated qualitatively with the aid of leading domain experts. Three criteria were raised, and an expert panel with 30 experts above was assigned to score these criteria. The experts were free to give any score between 0 and 1 to express their agreement on the three following criteria, where 1 indicates excellent agreement and 0 indicates strong disagreement:

- *Scientificity* Does the method reflect the strength of interdisciplinary interactions truly and objectively?
- *Integrity* Does the method fully consider the measurement angle of interdisciplinary, and can it comprehensively reflect the cross-integration of knowledge between two different disciplines from all aspects?
- *Innovation* Is the indicator system innovative compared to traditional interdisciplinary measurement methods? Fig. 7 shows the results.

From Fig. 7, it can be concluded that the difference between the maximum value and the minimum value of three evaluation indexes is only 0.3, which indicates that the distribution of index scores is relatively concentrated. The average values of scientificity and integrity are greater than the median, indicating that most experts have higher scores (greater than the average), while the average value of innovation is slightly less than the median. In addition, the average values indicate that experts strongly recognize the scientificity and integrity of our method. Although our method needs to be improved, the average score of most interdisciplinary measurement methods is more than 0.7, which is considered acceptable (Zhang et al., 2018).

Discussion and conclusions

In this paper, we proposed a measurement model of interdisciplinary between two specific disciplines that takes both the citation relationships between disciplines and the semantic relationships found in research publications into account. Within the framework, citation analysis that draws upon direct citation and bibliographic coupling is used to construct a citation network representing the interactions between two given disciplines, and the Jaccard index is then used to measure the strength of those interactions. The semantic analysis involves the combination of an LDA topic model and the Word2Vec model. LDA mines keywords and Word2Vec builds multi-dimensional discipline-keyword vectors that are used to accurately estimate the similarity of the document content between two disciplines. Compared with other methods that measure interdisciplinary interactions with a single dimension, we find using both methods makes up for the shortcomings of each. Most particularly, citation analysis can only reveal relatively shallow interdisciplinary relationships.

This work has three major contributions: (1) Our framework focuses on quantifying the degree of interdisciplinarity between two specific disciplines; however, our predecessors have largely focused on the study of the interdisciplinary nature of a single object—i.e., a paper, an author, a journal, a scholar, an institution. (2) Our study directly applies the concept of mixed methods combining citations and semantic analytics in the measurement and modeling of interdisciplinary interactions between disciplines. (3) In constructing a mixed methods approach, we paid more attention to the accuracy of semantic analysis because terms and words can differ across disciplines. At present, existing mixed methods are more represented as "citation" plus "co-word"; however, many studies have shown that traditional text analytics are not as good as word embedding for semantic analysis (Hu, Qi, et al., 2018). Therefore, in our study, direct citations and bibliographic coupling were applied to trace the knowledge transfer process. Meanwhile, an LDA model combined with a word embedding model was used to gauge the effects of knowledge integration and diffusion.

Our case study and subsequent empirical validations demonstrate the reliability of the methodology by showcasing six different examples of LIS paired with a range of other disciplines—some with high levels of interdisciplinary interactions, others not. The main conclusions of this paper include: (1) "Management" and "Information Systems" have relatively strong interdisciplinary interactions with LIS, while "Geography" and "Education" have relatively weak connections; and (2) the multi-dimensional index system of comprehensive citation analysis and semantic analysis proposed in this paper is able to measure the interdisciplinary interactions between two disciplines more comprehensively and accurately than four mainstream baselines.

Technical implications

Citation analysis has been widely used in interdisciplinary research. However, most citation analyses are limited to interdisciplinary citation relationships, and the interdisciplinary relationships excavated are shallow and rough. In this paper, we combine citation analysis with semantic analysis such that we not only consider the knowledge transfer process but also the effect of knowledge integration and diffusion. This design can be applied to both research on interdisciplinary, or it can be used to explore other types of relationships.

Notably, traditional keyword analysis tends to ignore contextual semantic relations. In this paper, we combined an LDA topic model with a Word2Vec model to capture the distribution characteristics of disciplinary keywords and to measure the strength of interdisciplinary interactions based on keyword vectors. Moreover, this combination is suitable for large data sets and other semantic analysis problems.

Possible applications

Compared with other methods, our framework has some distinctive contributions. Three applications of this framework are immediately apparent to us.

- Our framework can be applied to academic information retrieval and recommendation systems to enhance the diversity of the search or recommendation results. For instance, if a user retrieves literature associated with a certain discipline through a query, our method could be used to rank the papers of other disciplines according to the strength of the interdisciplinary interactions between the queried discipline and the ranked disciplines.
- Our method can be used to measure the interdisciplinary interactions between any two disciplines. Therefore, our framework can be extended to a large-scale literature database. In this way, it could be used to mine the cross-relations among all disciplines and a comprehensive interdisciplinary knowledge graph could be built to promote interdisciplinary academic cooperation and knowledge flows.
- Our framework can help universities and research bureaus restructure their organizations. For example, when two disciplines have very strong disciplinary interactions, universities might consider merging or fostering partnerships between the corresponding organizational units.

Limitations and future studies

In this paper, we attempted to measure the strength of interdisciplinary interactions from the perspective of citation relationships and semantic relationships. Although our work supplements existing research problems, it still has some shortcomings and limitations that require further investigation and improvement. Generally speaking, the following points should be considered in the subsequent research: (1) Enriching data samples. The publications of WoS database were selected as the data samples in this study, which will inevitably have led to the omission of relevant literature in the field. At the same time, in the process of empirical study, the age of selected papers stopped at 2019, which does not show the most recent developments in interdisciplinarity. In the future, we plan to assemble academic literature over different study periods so as to chart the dynamics of interdisciplinary with a larger sample. (2) Mining the citation content. In this paper, we only considered simple citation relationships, while ignoring the relevance of citation content. In the future, we may combine the text analysis method with the citation content to more deeply explore interdisciplinary relationships. Doing so might further perfect the measurement of interdisciplinarity. (3) Consideration of multidisciplinary articles. In our data pre-processing, we made no attempt to remove duplicate articles retrieved under searches of different disciplines, which may have skewed the results of our calculations. To overcome this problem, it will be necessary to develop a more comprehensive system that can fully consider the impact of the same article being coded (in WoS or any other index) to more than one discipline. This we leave to future work.

Acknowledgements This work was supported by the National Science Foundation of China [Grant No. 71673086; 71774013]. Our heartfelt appreciation goes to Changtian Wang for his contributions to this paper.

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