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THE PERSONALIZED LEARNING PATHS FOR DIGITAL MEDIA TECHNOLOGY EDUCATION BASED ON BIG DATA

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Abstract. The paper intends to study the evolution of domain knowledge by studying the spatial-temporal collaborative model. A joint knowledge network model based on the time-space domain is proposed to represent the knowledge base. The skeletal clustering algorithm analyzes the evolution of knowledge networks over the years. According to the concept of the evolution process of knowledge, the paper makes a connection and path analysis of its evolution track. An empirical study of the digital media field is carried out. The results show that the algorithm proposed in this paper can extract the evolution trajectory of domain knowledge that varies with year. The path of knowledge evolution can show the correlation between research topics, hot topics, core literature, the evolution law of research topics and research methods of multiple disciplines, and the cross-characteristics of multiple disciplines.

Key words: Knowledge evolution; Evolutionary pathway; Spatio-temporal correlation; Learning path; Digital media technology

1. Introduction. In the big data environment, various disciplines are developing rapidly, and research papers in various disciplines are increasing rapidly. Therefore, an accurate and practical grasp of the trajectory of knowledge generation, development, evolution, and extinction is helpful for researchers to grasp the research focus of this field accurately and quickly find its key and frontier problems. Identifying the research hotspot and its evolution law in this field can realize efficient resource allocation of scientific research, support scientific decision-making and promote scientific innovation. In this context, it is essential to determine the path of knowledge evolution in the subject area.

At present, many scholars have used different methods to study the generation and visualization effect of the knowledge evolution path. The primary path method based on the citation network measures the connectivity of a loop less network by using the neutrality between nodes composed of the nodes with the most significant number of vertices. The primary research method is to use the global connectivity of the citation network to extract the primary way and to study the development trend and core literature, essential people and significant events in the academic field. The primary path analysis method is used to explore the data enveloping analysis method.

Literature [1] explores the knowledge diffusion path in data quality based on primary path analysis. Literature [2] uses main path and edge clustering methods to identify the dominant knowledge flow and activity orientation in science and technology adoption research. Literature [3] uses the method of three main channels to initially show the main clues of knowledge evolution in mobile libraries. Literature [4] shows its rich disciplinary evolution characteristics by extracting the agglutinite and structural cave groups associated with the primary pathways. Literature [5] proposes a research idea based on title clusters, that is, by clustering and classifying keywords to extract hidden information in the text. Many researchers have adopted the method of coward-based clustering to study knowledge evolution. Literature [6] uses time-series mapping technology to express and analyze topics dynamically based on clustering. Literature [7] uses the LDA method to represent topics' deep semantic characteristics and constructs the topics' evolution trajectorypics in each period. Literature [8] studies the evolution trajectory of topics and proposes a symbiotic network of topic probability distribution based on weights. The co-word clustering method based on SciMAT was used to carry out the

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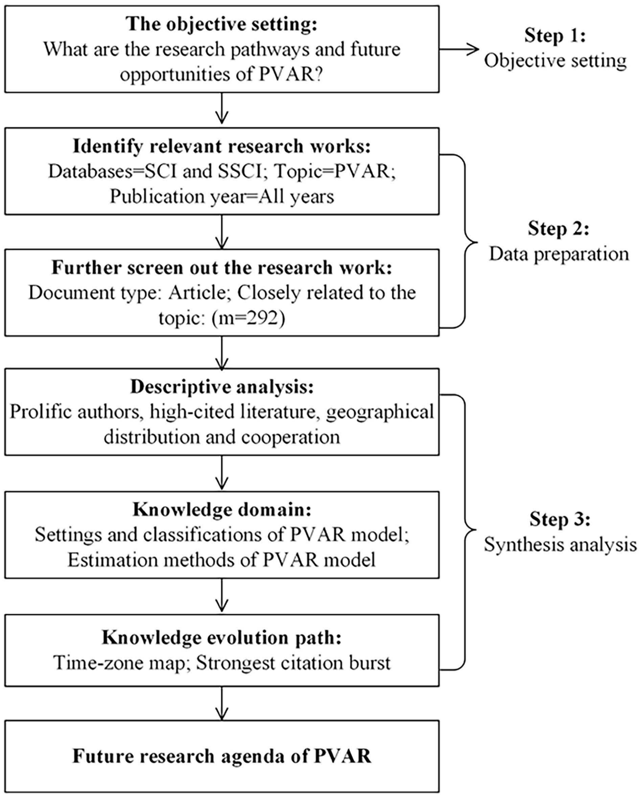

Fig. 2.1: *Reflections on the way of knowledge evolution.*

trajectory diagram of the dynamic evolution of ISLS research hotspots in literature [9], the Jaccard coefficient measured the similarity of topics, and the current ISLS research hotspots were determined by constructing the evolution trajectory of topics. Literature [10] establishes a spatio-temporal scale-oriented domain knowledge evolution situation analysis model and connects it with the knowledge evolution process. The existing research ignores the non-key academic resources in the citation network, and it isn't easy to dig out the evolution law of the topic from the evolution track of academic resources.

This project intends to study the research idea of knowledge evolution in the time-space domain: the classical knowledge network is taken as the research object, and the shortest circuit with the best skeleton characteristics is taken as its evolutionary track to construct a complete knowledge evolution context in time-space scale [11]. This project intends to take academic papers in the digital media industry in CNKI as the primary research object by constructing an annual time series and extracting evolutionary trajectories based on bone clustering to study and analyze the development process.

2. Model framework. The research ideas of this paper can be summarized in Figure 2.1. This paper consists of four stages: data collection, primary path analysis, concept integration and knowledge evolution path construction. Firstly, the paper extracts "title," "keywords," and "abstract." The pauses in the sample were reduced and "dried." Then, the topic modeling method extracts keywords and builds a vocabulary dictionary. This paper uses isi.exe and CitNetw.exe to process data. The global mainstream route method (GMP) is selected, and the path between each junction and each node is extracted by an exhaustive method [12]. The path with the highest arc weight is the main line, and its literature is regarded as the essential reference material. The document-subject word matrix is established. The vector space modeling method is used to measure the similarity of the thesis. They are sorted according to their similarity with core papers to form appropriate core document nodes. In the framework of SATI, elements such as "keywords," "titles," and "abstracts" are extracted in a particular order, and then semantic mining of each node is carried out through topic modeling to realize the expression of each node topic in the text. Finally, the paper describes the research links in the text, thus establishing a text-based approach to knowledge evolution.

2.1. Knowledge network module. A knowledge network is essential for studying knowledge development in knowledge graphs. A knowledge network comprises nodes and edges, in which nodes represent knowledge elements and edges represent knowledge connections between entities. According to the difference of entity units, the nodes can be papers, patents, books, keywords, etc. According to the relevance of knowledge, the edge can be divided into reference relationships, symbiotic relationships, and cooperative relationships [13]. In this method, domain keywords are treated as nodes and evolutionary weights as edges, which are modified. Compared with reference networks, co-lexical networks can reflect the evolution of entity concepts in networks more directly and efficiently. The knowledge network established in this project is a weighted undirected network, and its research content is divided into two parts: The first is to evaluate this kind of knowledge network and its importance on the network diagram, such as keyword frequency, node degree, intermediate centrality, etc. The second is the shortest path, critical path and average path length are studied based on node connection. Network node analysis is often used to obtain the distribution of network topics, while network path analysis is used to predict the development direction of domain knowledge and find research hotspots.

2.2. Knowledge base vocabulary extraction. Research on Chinese vocabulary extraction has dramatically progressed, and relatively perfect methods have been developed. Among them, the Chinese automatic identification system NLPIR of the University of Chinese Academy of Sciences is the representative. This section discusses using the NLPIR to extract terms and data from files. Firstly, the text base related to a specific domain is collected, and the Key Extract Get Keywords algorithm in NLPIR is used to extract the vocabulary of a single text and store it in HashMap as a key-value pair. The key represents the keyword [14]. The value indicates the frequency of keyword occurrence and the number of keywords is collected. The first step is to extract the file, store it in the hash map when the first keyword appears, and set the key value to 1. If the keyword already appears in the hash map, the corresponding value of the keyword is increased by 1. Keywords in all files up to the current year are calculated. Finally, the keywords are sorted in descending order according to the value, and the N keywords with the highest frequency are listed as the domain words collection. The process of lexical extraction is shown in Figure 2.2. (The image is quoted in Intelligent RFQ Summarization Using Natural Language Processing, Text Mining, and Machine Learning Techniques).

2.3. Construction of time-space joint knowledge ne twork. The spatiotemporal collaborative knowledge network describes the change of knowledge with time in a dynamic process by establishing the spatiotemporal knowledge network. This project divides the collaborative knowledge network into two stages: generating a new knowledge network every year and building a continuous network based on multiple network nodes that have emerged in the last year [15]. The core work of knowledge network construction is to extract the relationship weights among network nodes. An evolutionary relationship can be regarded as an inter-entity relationship, depending on the text's lexical meaning and occurrence times. Over time, the degree of evolution has increased. This paper proposes the definition of evolutionary relation, that is, given file K, document knowledge concept entity sequence is represented as $R=\{r_1, r_2, r_3, \ldots\}$, and formula (2.1) is used to calculate the semantic distance between two entity concepts r_i and r_j in series R.

$$\operatorname{dis}(r_i, r_j)=\sum_{T_i \in R}|j-i| / n$$

i and j represent a particular class of knowledge in the series. And n represents a pair of information in a particular category in the series. The lower the semantic distance, the higher the degree of evolution between the two concepts r_i and r_j. A meaningful distance threshold σ is set in the test. If the relative distance between two information pairs is more significant than a particular critical value, they are evolutionarily related; otherwise, they are not evolutionarily related. If the node r_i is evolutionarily related to the node r_j, then there must be a connection path in the knowledge network of node pairs. The definition of evolutionary distance is given in

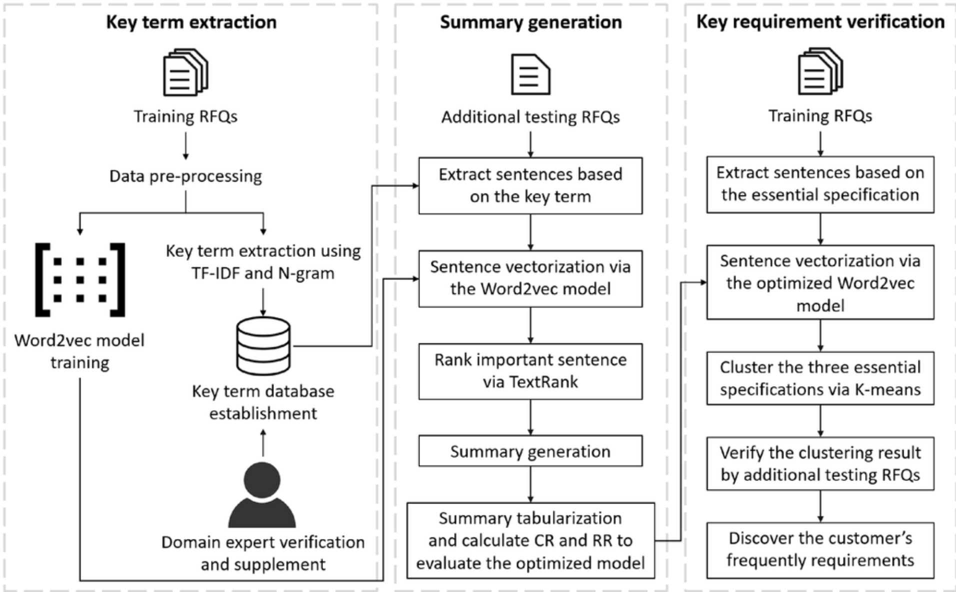

Fig. 2.2: *Term extraction process.*

formula (2.2):

$$\operatorname{evo}\left(r_i r_j\right)=\exp \left(\left[\sum_{r_i r_j \in \bar{K}} \operatorname{dis}\left(r_i, r_j\right)\right)^2 / \left(2 m^2 \gamma^2\right)\right] / m^2$$

$\bar{K}$ represents the set of documents in which the entity concepts r_i and r_j exist. m represents the number of occurrences and $\operatorname{evo}(r_i r_j)$ has a low value, indicating that the evolution from r_i to r_j is relatively simple. The detailed process of extracting evolutionary relationships is shown in Figure 2.3. Then, the extracted keywords are input into the NLPIR automatic segmentation software to form a customized dictionary so that the software can be coarse granular segmentation [16]. Segmentation of individual text. User-defined words are filtered in the segmentation results to initialize keywords in the file. This is then combined with the contiguous neighboring keywords in the series to obtain the new nonoverlapping sequence R'. Then, the relationship between the keyword pairs in the sequence R' is analyzed. For example, there are two keywords r_i and r_j in R', both of which are stored in the form $\{r_{ij}, e_{ij}, n_{ij}\}$. Where r_{ij} is a pair of associations, e_{ij} is the semantic spacing of associations in a file, and n_{ij} is the number of occurrences of a pair of associations. The association pairs in the literature were statistically analyzed. n_{ij} and n_{ij} were accumulated for the association pairs that occurred frequently. Finally, the average semantic distance and occurrence time between the two groups of associations are obtained. Formula (2.2) calculates the evolutionary distance between the correlations and determines the weights between the correlations.

A knowledge network based on the time-space scale is established with keywords as nodes and evolutionary distance as weights. Figure 2.4 shows the joint knowledge network on a time-space scale over three years. The dots represent the knowledge of something. The larger the diameter of the circle center, the more critical the information held in the network [17]. The connections between nodes represent evolutionary connections. When the weight value is low, the nodes in the network are close to each other, indicating that the evolution of the two is higher. The dotted lines show the intersecting views of knowledge in each year's knowledge network. These repeated knowledge concepts establish the knowledge evolution relationship between successive years.

2.4. Skeleton cluster analysis. This paper focuses on extracting an optimal evolutionary route from this knowledge network. An ideal evolutionary trajectory can be regarded as the interconnection of multiple

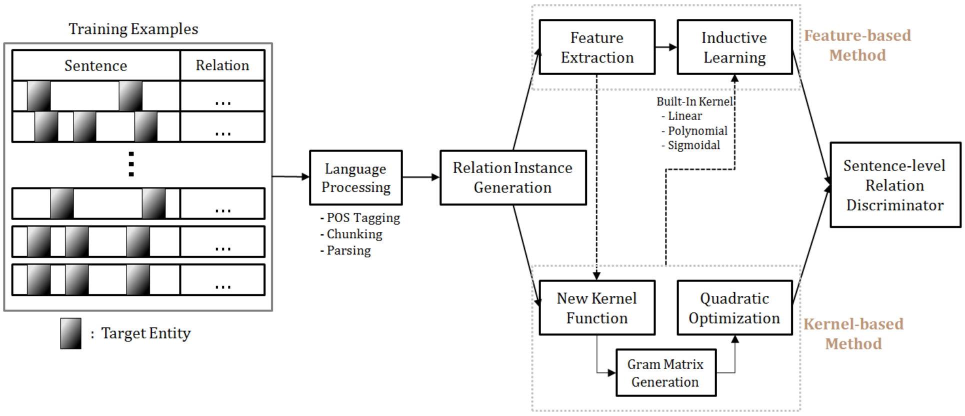

Fig. 2.3: *Evolutionary relationship extraction process.*

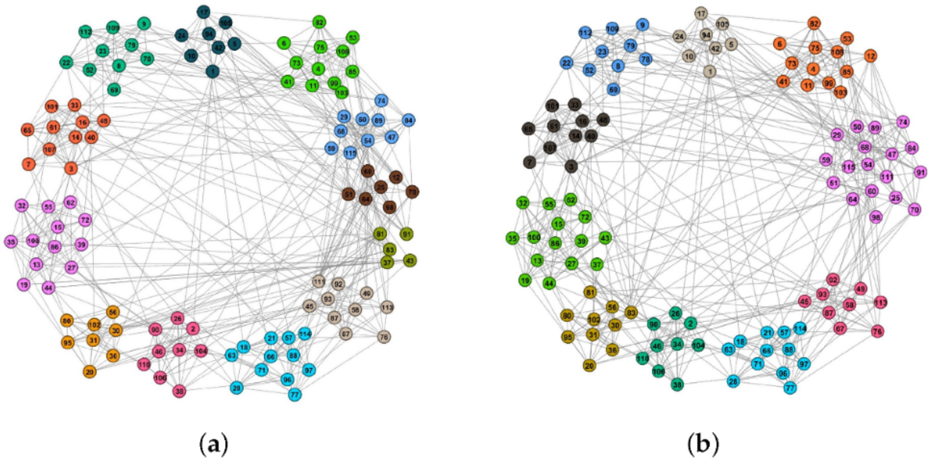

Fig. 2.4: *Space-time joint knowledge network structure.*

network systems, and the framework of the network system plays a role in supporting the network system, so the perfect network system must have the characteristics of centrality and connectivity. A knowledge network model based on ”bone clustering” is established. Its general idea is: ”partial aggregation, global correlation.” Each cluster can be regarded as a knowledge topic, and its core node should be dispersed among multiple knowledge topics as much as possible. This core node can become the clustering center of a topic to achieve the best topic clustering. ”Overall association” connects all nodes in each hierarchy to form an overall framework. In principle, the whole structure should be able to cover the entire knowledge network fully and simultaneously, ensuring that the sum of topic clustering effects of each part reaches the maximum.

The shortest path is seen as the best evolutionary path. The shortest path refers to the minimum cost required to get from one node to another, which can be regarded as the shortest path from one node to another [18]. Because the shortest circuit corresponds to the starting and ending points of evolution, it is necessary to use the clustering method of the molecular evolutionary tree to study the importance of various shortest circuits in the evolutionary process. A node cluster comprises multiple nodes; one node should be a good centrality, and the neighboring node is the cluster's core, thus forming a knowledge body. The detailed expression of the node clustering coefficient is expressed in the expression (2.3):

$$CH(r) = \sum_{z_i \in Z} djs\left(z_i, r\right)/Z_n$$

CH(r) is the clustering coefficient in trunk node r; Z is the subject related to r; Z_n is the number of nodes included in topic Z; Where dis $(^*, ^*)$ is the shortest between the nodes. When CH(r) cluster coefficient is the lowest, r is regarded as the core of the topic cluster. The whole skeleton was clustered and the best skeleton was selected. A specific calculation formula is expressed in equation (2.4):

$$SH(R) = \sum_{r_i \in R} CH\left(r_i\right)/Z_n$$

Z_n is the number of backbone nodes included in the backbone R. When the average cluster factor $SH(R)$ in a chain R is the lowest, the chain it represents is the optimal evolutionary chain.

3. Experimental research.

3.1. Experimental data. This paper selects the field of digital media as a new subject to conduct empirical research combined with the development of the subject and the current hot research direction. This research followed the following procedures: First, CNKI was selected, and the search keywords were "media" and "digital media." This paper analyzes academic papers from 1997 to 2022 using "abstract" and "keyword" as search items. Articles in CAJ format are then downloaded by year and stored as the corresponding annual directory for "1997-01". If many papers appear in a given year, 300-500 papers are selected as the standard according to the number of paper downloads and citations. Secondly, using the "save as" function provided by CAJ Viewer, the conversion of the CAJ file to a TXT file is realized to facilitate the running of the Java program. Some of the papers published in the early stages are stored in images, so the process will soon produce confusing code. It selects 5,214 typical papers published between 1997 and 2022. These articles can reflect the current development trend and research progress of digital media.

3.2. Test results. The experimental part is based on the knowledge network and integrates the academic papers published in digital media for many years to establish a complete subject knowledge network. According to the word frequency and node degree of the network, it is comprehensively sorted out. This paper analyzes the evolution of the knowledge of the digital media knowledge network over the years and extracts the evolution path to show the development course of the digital media field.

Firstly, NLPIR automatic segmentation technology is used to select 10 keywords for each text search result. After analyzing all the keywords in the text and their corresponding frequencies, 953 keywords with higher frequencies are selected and named "digital media." Table 3.1 lists the 10 most frequently used keywords, among which "digital media," "media," and "traditional media" are all words with vital representative significance in digital media. In a sense, this illustrates the effect of these words' extraction.

Integrating all digital media publications from 1997 to 2023 establishes and studies a complete knowledge network covering 27 years at the nodal level. A database of 953 knowledge words was formed, and the order of related topics was extracted from the literature [19]. Use formula (2.2) to treat keywords as network nodes. The evolutionary distance is the network edge that establishes the knowledge network.

Node degree reflects the number of associations of nodes in the knowledge network. The more associations there are, the higher the importance of the keyword. Figure 3.1 shows the 116,274 knowledge relationships corresponding to 953 keywords, in which the degree of keywords is distributed in a long tail, indicating that there is a small part of the core knowledge with high nodal, while most of them are low nodal, and this information are the "Bridges" connecting this information.

Table 3.2 lists an index of some of the top 20 subject words of the year. Through the statistics of the information in the list, it can be found that in the news reports of 1997, the keywords are "TV," "radio," and "audiovisual teaching." After 2007, "network," "Internet," "mobile phone," and other keywords have appeared in people's vision. Keywords such as "media" and "TV" are widely representative in the field and frequently appear yearly. It also reflects the evolving digital media landscape with the times.

Table 3.1: *List of top ten keywords in integrated word frequency in digital media.*

Serial number	Keyword	Occurrence frequency
1	Digital media	871
2	media	738
3	Old media	695
4	Intel	565
5	news	426
6	diffuse	371
7	Digital television	350
8	network	339
9	advertisement	326
10	TV	310

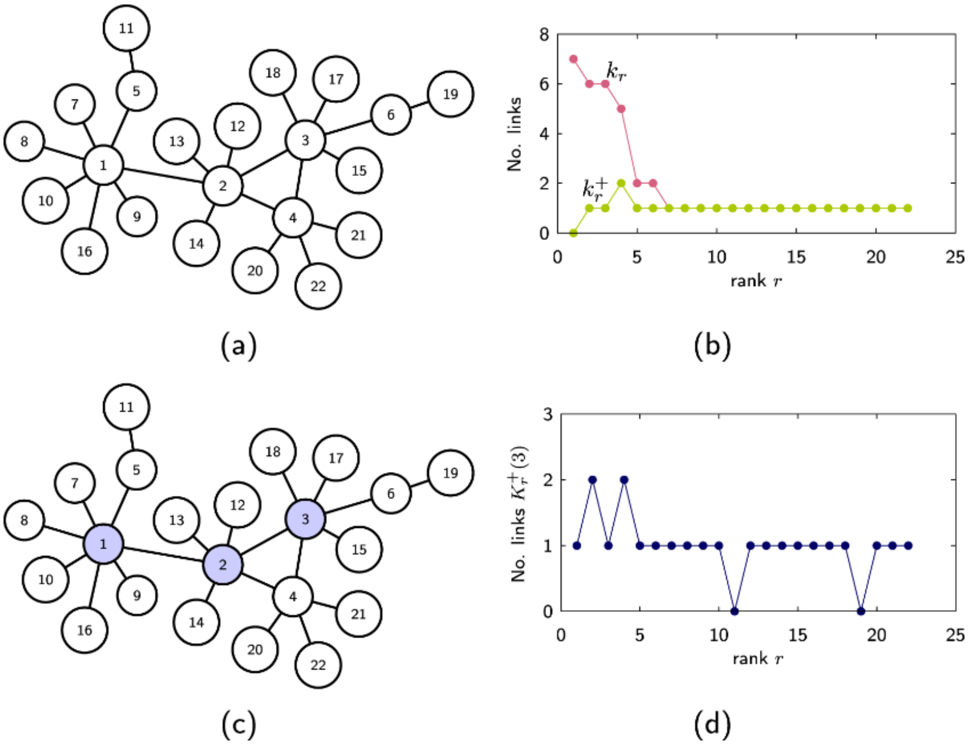

Fig. 3.1: *Node degree distribution curve of the knowledge network.*

Table 3.3 lists the typical evolution trajectory of digital media knowledge structure from 1997 to 2022. With the development of digital media, there are many new things and ideas. From 1997 to 2000, digital media was dominated by traditional media such as TV, radio and newspaper, and used a large number of keywords such as "audiovisual teaching", "teaching media," and "distance teaching" in teaching. At the end of its evolution in 2001, "Microsoft" became the company that most promoted the development of digital media, and it was also the combination of computer technology and digital media [20]. During 2002-2007, with the increasing use of information technology such as digital processing and image processing, keywords such as "notebook" and "network user" indicate that network technology is becoming more and more perfect. Digital media has been in the "digital age" since 2007. Among them, "digital radio," "digital television," "digital music," "digital information," and so on have poured into the public's attention in batches. Since 2017, there has been a

Table 3.2: *List the top 20 knowledge network node degree keywords in some years.*

Serial number	1997	1998	2007	2012	2017	2022
1	TV	media	network	media	media	TV
2	radio	multimedia	TV	network	network	radio
3	media	computer	media	digit	TV	media
4	computer	TV	digit	TV	digit	computer
5	Audiovisual materials	imago	imago	digitalization	Internet	Audiovisual materials
6	imago	network	computer	radio	digitalization	imago
7	TV	media	network	media	media	TV
8	radio	multimedia	TV	network	network	radio
9	media	computer	media	digit	TV	media
10	computer	TV	digit	TV	digit	computer
11	Audiovisual materials	imago	imago	digitalization	Internet	Audiovisual materials
12	imago	network	computer	radio	digitalization	imago
13	TV	media	network	media	media	TV
14	radio	multimedia	TV	network	network	radio
15	media	computer	media	digit	TV	media
16	computer	TV	digit	TV	digit	computer
17	Audiovisual materials	imago	imago	digitalization	Internet	Audiovisual materials
18	imago	network	computer	radio	digitalization	imago
19	TV	media	network	media	media	TV
20	radio	multimedia	TV	network	network	radio

diversified development trend in the code media industry. ”Game industry” and ”network game” are significant terms for the vigorous development of China’s network game industry. Keywords such as ”virtual world,” ”interactive experience,” ”home theater,” and ”mobile intelligent terminal” all indicate that the development of digital media is more closely related to our daily lives, and it also indicates that our society has entered a new era of intelligence and popularization of literature and art. The general evolution trend of this route is consistent with the general evolution direction of the ten routes, which indicates that the evolutionary context of this route is credible.

4. Conclusion. This project uses the period from 1997 to 2022 as an example to conduct an empirical study of Chinese academic papers on digital media using the time-space joint model. Firstly, the comprehensive data modeling is carried out from the aspects of node word frequency and node degree, and the comprehensive knowledge structure and feature extraction are carried out. The skeleton clustering method establishes the joint knowledge network on the time-space scale. The corresponding year information is extracted and concatenated—an in-depth analysis of its evolution in several years. The research results show that the development process of China’s digital media can be roughly summarized as follows: from ”TV,” ”radio” and ”newspapers” in the early 1990s to 2007, all kinds of traditional media have turned to digital media, and produced ”digital games,” ”digital animation,” ”digital audio and video,” ”digital publishing” and ”digital learning” and other main branches.

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Table 3.3: *Knowledge Evolution trajectory in a typical digital media.*

A given year	Evolutionary path
1997	Newspaper media, advertising media, multimedia media, audiovisual media, modern educational media, video media, television signals, software, database
1998	Database, video, television signals, VCR, film, educational media, animation production, television, radio
1999	Radio, mass media, distance learning, television media, paper textbooks, radio stations, newspapers, information networks, information services
2000	Information services, advertising, audiovisual books, audiovisual education, electronics, public media, media, television news, newspaper advertising
2001	Newspapers, radio, TV, VCR, tape recorder, games, Microsoft
2002	Microsoft Corporation, electronic publications, multimedia technology, computer technology, recording technology, audiovisual teaching materials
2003	Audiovisual materials, audiovisual materials, super media, digital signals, information technology, communication technology, digital processing
2004	Digital processing, communications technology, television communications, image processing, print media, magazines, advertising
2005	Magazines, newspapers, color television, multimedia, data, optical discs, recording media, computers, networks, microprocessor chips
2006	Microprocessor Computers, radio, television, video conferencing, computers
2007	Computer, digital media, Internet, Information industry, communication technology
2008	Communication technology, digital information, information technology, distance learning, portable computers, mobile phone users
2009	Internet users, multimedia materials, computers, digital technology, Digital century, media advertising
2010	Digital age, network media, audiovisual media, film and television media
2011	Film and television, radio, Internet art, electronics, broadband network, Internet media, media ecology, interactive media, classical art
2012	Traditional media, television industry, cable television, terminal devices, computers, software development, games, information consulting, E-mail services
2013	Client software, software, television, film and television, Web, communication technology, radio, television
2014	Television, radio, electronic messaging, mobile phones, computers, communication technology, news media
2015	News media, distance learning, e-commerce, digital, audio
2016	Audio radio, mobile TV, web games, web advertising, web portals, video advertising, television, game industry
2017	The game industry, the record industry, online games, databases, contemporary media
2018	Contemporary media, Internet, traditional media, Internet media, digital advertising, cultural industry, music industry
2019	Recording industry, information network communication, mobile phone network, Internet, digital technology, network operator
2020	Internet operators, information services, blogs, Media, Web resources
2021	Internet sources, digital audio, classical TV programs, traditional media, media, Internet, communication technology, computers, home theater
2022	Virtual world, Internet, media, traditional media, mass media, media age, mobile intelligent terminal
2023	Interactive experience, pictures, printing technology, digital media, media, radio, newspapers, e-magazines

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