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Identification of Emerging Technological Hotspots from a Multi-Source Information Perspective: Case Study on Blockchain Financial Technology

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Abstract: In recent years, propelled by societal transformations and technological advancements, emerging technologies founded upon diverse disciplines such as financial and information technology have rapidly evolved. Identifying the trends associated with these emerging technologies and extracting their salient topics is crucial in order to accurately grasp the developmental trajectory of these tools and for their efficient utilization. In this study, we chronologically categorize information derived from five types of multi-source data, including journal articles, patent inventions, and industry reports, into distinct periods. We employ the LDA (Latent Dirichlet Allocation) topic model to identify emerging technological themes within these periods and utilize a dual-index theme lifecycle analysis method to construct a hotspot theme distribution map, thereby facilitating the extraction of significant themes. Through empirical research on blockchain financial technology, we ultimately identify 22 thematic areas of blockchain finance and extracted eight prominent themes, including financial technology, cross-border payments, digital invoices, supply chain finance, and decentralization. By analyzing these themes alongside their respective popularity levels, we validate that the methods above can be used to effectively identify emerging technological hotspots and illuminate their developmental directions.

Keywords: theme identification; emerging technologies; LDA topic model; dual-index theme lifecycle analysis; blockchain finance

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1. Introduction

In recent years, the rapid development of emerging technologies grounded in financial technology, information technology, and various other disciplines has significantly influenced the evolution of traditional industries, impacting societal consciousness, perspectives, and lifestyles. The continuous integration and advancement of various information and intelligent technologies have shaped the nascent forms of today's emerging technologies, which are characterized predominantly by technological convergence [1,2]. Some scholars refer to these innovations collectively as "Fintech", highlighting the intrinsic relationship between emerging technologies and the broader field of financial technology. Electronic finance has evolved significantly from its initial stages to the comprehensive application of various internet information technologies in the present day. The profound fusion of "finance and the internet" underscores the prominent manifestation of convergence within the financial technology sector [3].

From the composition of development plans across different fields, it is evident that plans related to emerging technologies are increasingly shifting from micro-level initiatives to ones pertaining to industry support and strategic domain planning [4]; thus, zemerging technologies act as a central thread interwoven through strategy, industry, and technology.

Identifying the themes of emerging technologies and engaging in early strategic positioning not only enables the timely tracking of technological dynamics, but also allows for the anticipation of potential trends and future opportunities for development. This is vital for the progress of a nation or region and will significantly influence its strategic developmental agenda [5]. However, the inherent uncertainty, diversity, and complexity of emerging technologies, in addition to the ambiguity of their characteristics, pose considerable challenges in accurately identifying these themes [6]. Consequently, the accurate and comprehensive identification of emerging technological themes has recently emerged as a focal point of scholarly attention.

2. Literature Review

2.1. Research on Identification Methods for Emerging Technologies

The identification, evolution, and monitoring of emerging technologies have persistently remained focal points of inquiry within governmental, corporate, and academic spheres. Methods for discerning emerging technologies and their themes can be categorized into two principal approaches: the first encompasses qualitative research methodologies, which predominantly rely on the subjective judgments of experts, such as the Delphi method [7,8], expert brainstorming [9,10], and technology road mapping [11–13]; the second comprises quantitative research methodologies, which leverage bibliometrics and data mining to analyze scholarly papers and the patent literature. These quantitative approaches are primarily divided into thematic keyword and bibliometric analysis, citation network clustering, and text-mining techniques [14–16].

Of the qualitative judgment methods, the Delphi method is the earliest and most commonly used; however, its inherent limitations, such as strong subjectivity and high cost, have gradually reduced its frequency of use. To address these shortcomings, improved qualitative identification methods based on the Delphi method have been proposed [17,18]. For example, Shen [19] combined the fuzzy Delphi method with the Analytic Hierarchy Process (AHP), and Bildosola et al. [20] built an emerging technology theme selection framework based on technology roadmaps and real options. Huang aimed to optimize the traditional qualitative identification process and avoid subjective expert scoring [21]. However, these qualitative methods still have their limitations; on the contrary, quantitative methods can enhance the authenticity and objectivity of identification.

Quantitative methods often search the abstracts or keywords of existing papers or patents for topic words and literature statistics to identify themes in emerging technology fields. The most representative method is J. Kleinberg's burst detection algorithm [22], which has been incorporated into tools like Network Workbench and Citespace II [23]. Citation network clustering analyzes the citation networks and coupling networks of papers or patents, clustering them based on similar themes. Liang Yongxia et al. investigated citation analysis theory from the perspective of knowledge flow and conceptual connections [24]. Li Bei et al. established an emerging technology identification model with an associated indicator system based on the core characteristics of emerging technologies and the patent literature. The authors employed patent-citation-coupling clustering and conducted an empirical study in the domain of nanotechnology [25]. Text-mining analysis has evolved with the proliferation of data mining and text analysis technologies, prompting an increasing number of scholars to apply such methodologies to identify the themes and analyze the developmental trends of emerging technologies. Common techniques include SAO structure extraction, vector space models, LDA topic models, and machine learning. Notably, Li Xin [26] and Yang Chao [27] utilized the SAO structure, specifically the "Subject–Verb–Object" configuration, to identify emerging technologies through semantic analysis. Ren Zhijun [28] and Dong Fang [29] employed LDA topic modeling for the identification of emerging technology themes, establishing probability distributions of several associated themes and further refining this identification through the integration of various metrics and evaluative criteria.

In summary, qualitative identification relies on the practical experience and subjective judgments of experts, for example, via the Delphi survey method, which has certain subjectivity limitations. Quantitative analysis, on the other hand, is primarily based on bibliometrics and data mining. It involves word association analysis and co-occurrence probability analysis on massive amounts of literature data, and thus can objectively reflect data characteristics. However, it often faces issues such as single data sources and an unclear categorization of themes in terms of importance.

2.2. Research on Blockchain Financial Technology

With the continuous development and improvement of emerging technologies, blockchain technology has shown great potential and broad application prospects in the financial field. The initial innovative models representing the field of blockchain finance technology [30] have been developed for application in digital finance [31], supply chain finance [32,33], and financial risk regulation [34]. For example, Su Guihong [35] conducted an empirical analysis of the relationship between financial technology and digital innovation in enterprises, finding that financial technology has a significant promoting effect on digital innovation in enterprises. He Zhichao [36] explores the application of electronic invoices and digital payments in financial and tax systems, proposing a method to optimize and adapt these systems to the development trends in the digital economy. Zheng Dinghao [37] proposed a dual-layered governance path of "international+domestic" and "trade+regulation" based on the various risks arising from cross-border financial services. Mao, J. [38] suggests that supply chain finance not only promotes the healthy and stable operation and sustainable growth of enterprises but also amplifies this effect through the integration of digital technology.

Although the current academic research on blockchain finance technology is relatively comprehensive, it is predominantly focused on the development trends in individual topics and fails to recognize emerging topics, especially hot topics. For example, Liu, Yunmei et al. [39] conducted data mining on 759 related papers based on bibliometric data from the Web of Science. They conducted in-depth research on the application of blockchain technology in finance, employing co-word analysis, the dual clustering algorithm, and strategic coordinate analysis to explore hot topics in the field and predict future development trends. However, considering the rapid development of blockchain technology and its applications in the financial field [40], the paper fails to analyze the time dimension, with no attention being paid to development dynamics and future trends in the field.

To overcome these limitations, this paper combines multiple sources of information, such as paper data, patent data, and book data. It uses the LDA topic model to identify emerging technology themes and applies a dual-index theme lifecycle analysis method to extract hot topics. Thus, we take into account the dynamic and timely development of blockchain financial technology, ensuring that the data used are accurate and comprehensive. Ultimately, we reveal the development direction of emerging technologies through the interpretation of hot topics.

3. Emerging Technology Hot Topic Identification Method Based on Multi-Source Information

3.1. Research Approach

The general research approach of this paper is shown in Figure 1. The specific approach is as follows:

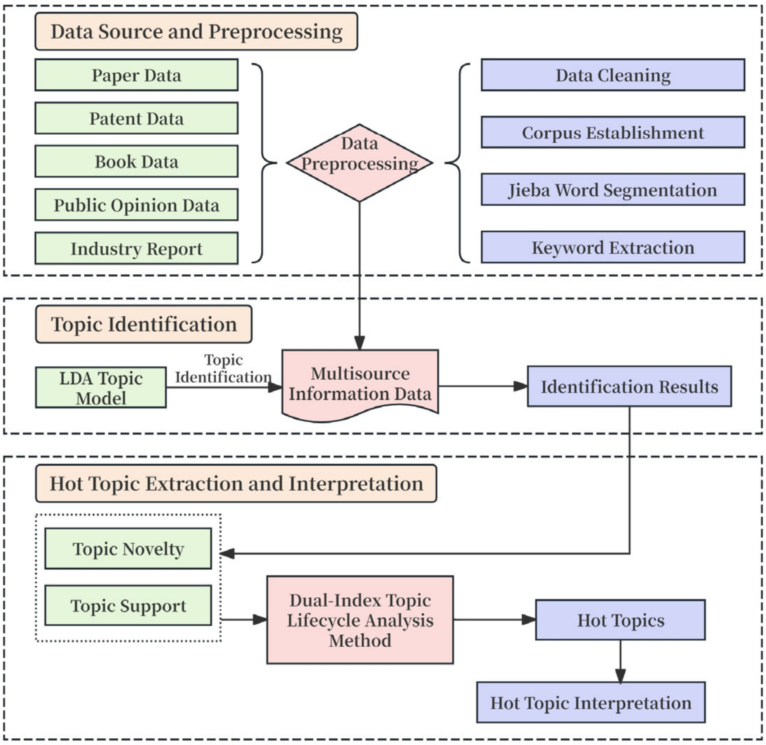

Figure 1. Research methodology for identifying emerging technology hotspots.

(1) Collecting data for empirical analysis from the China National Knowledge Internet (CNKI) database, the National Library catalog inquiry system, public opinion websites, and Chinese internet data information networks;

(2) Preparing the data via data cleaning, corpus establishment, Jieba word segmentation, and keyword extraction;

(3) Using the Jieba library to perform word frequency statistics to gain an initial understanding of emerging technology themes;

(4) Utilizing the LDA topic model to identify emerging technology themes from the preprocessed multi-source information;

(5) Extracting hot topics from identified themes by calculating their novelty and supportiveness using a dual-index theme lifecycle analysis method;

(6) Interpreting hot topics to reveal the future development direction of emerging technologies.

3.2. Research Methods

3.2.1. LDA Topic Model

A variety of methods have been developed for topic identification, including the TF-IDF method based on term frequency, the TextRank algorithm from web recommendation systems, and the PageRank unsupervised topic extraction algorithm. However, these methods primarily rely on the literal meanings of target terms for topic matching, often overlooking the deeper significance embedded within the text and failing to scientifically uncover the latent connections between themes and text.

This paper employs the LDA topic model for theme identification. Proposed by Blei et al. in 2003, the LDA model is a probabilistic topic modeling approach that can identify latent thematic information within large collections of documents or corpora [41]. It is structured in three layers: words, topics, and documents. The LDA model assumes that each word in each article is obtained through the process of "selecting a topic with a certain probability and selecting a word from this topic with a certain probability". Its core functions are to provide the topic of each document in a document set in the form of a probability distribution and to analyze these topic distributions by performing topic clustering or text classification. Specifically, for each document in the corpus, the LDA model undergoes the following generation process: First, for each document, a topic is extracted from the topic distribution. Next, a word is extracted from the word distribution corresponding to the selected topic. Finally, the above process is repeated until every word in the document is traversed. The LDA model is commonly used for identifying hidden thematic information in large-scale documents or corpus datasets. It simplifies the complexity of the problem by converting textual information into easily modeled numerical information (bag-of-words method) and ignoring the order between words.

As an unsupervised machine learning method, the LDA topic model demonstrates superior performance in analyzing semantic aspects of text compared to traditional topic mining methods, effectively managing to analyze large-scale unstructured document collections. Moreover, it can extract latent themes without the need for prior manual annotation of the initial documents. Therefore, applying the LDA model to document content analysis can effectively preserve the internal relationships within documents and scientifically reveal the evolutionary pathways between themes. The specific model is illustrated in Figure 2.

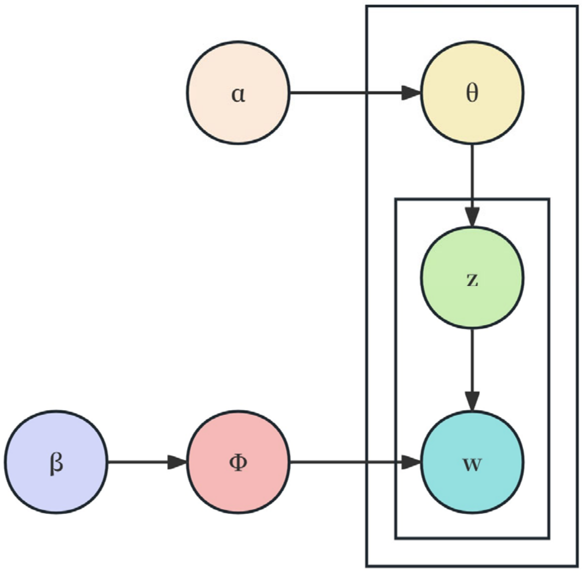

Figure 2. Architectural diagram of the LDA topic model.

In the LDA model, α and β are used to define the Dirichlet prior distributions, where α serves as the prior distribution parameter for θ, and β serves as the prior distribution parameter for φ. A common practice in parameter selection is to set α to an empirical value, such as 50/K, where K is the number of selected topics. This value is based on previous experiments and experience, and usually balances the performance and computational complexity of the model well. Alternatively, Bayesian estimation can be used to automatically adjust the value of alpha. β is usually set to a small empirical value, such as 0.01, which helps the model converge quickly during training and can better reflect the distribution of words in the topic. In addition, θ and φ represent the distributions of topics and topic words, respectively; z denotes the topics generated via the model, w refers to the final topic words generated, N indicates the number of words in the document, and M signifies the total number of documents.

The generative process of the topic model takes place as follows: First, a document of length L is selected from the global corpus. Next, samples are drawn from the prior distributions with parameters α and β to generate the distribution of topics θ for the document and the distribution of words φ for the topics. Typically, default values are chosen for α and β. Finally, topics z and topic words w are selected from the multinomial distributions parameterized by θ and φ, respectively. The joint distribution expression for all variables in the model is shown in Equation (1).

$$p(w, z, \theta_m, \varphi_k|\alpha, \beta) = \Pi_{n=1}^{N} p(\theta_m|\alpha) p(z_{m,n}|\theta_m) p(\varphi_k|\beta) p(w_{m,n}|\theta z_{m,n}) \tag{1}$$

Perplexity quantifies the uncertainty of the topics associated with a document and is employed in natural language processing to evaluate the clustering performance of the LDA model. A lower perplexity indicates a better clustering outcome. In the LDA model, the number of topics must be predetermined. To determine the most appropriate number of topics, perplexity is used to establish the optimal number of topics K for the dataset. The perplexity calculation formula is provided in Equation (2). Typically, when the decline in perplexity is no longer significant or reaches an inflection point, the corresponding value of K at that juncture is considered the optimal number of topics.

$$Perplexity(D) = exp\left(-\frac{\sum_{i=1}^{M} lnp(d_i)}{\sum_{i=1}^{M} N_i}\right) \tag{2}$$

3.2.2. Dual-Index Theme Lifecycle Analysis Method

The dual-index theme lifecycle analysis method is a method used to analyze the trend in theme evolution over time, combining lifecycle theory and theme models. Topic lifecycle analysis first uses topic models such as LDA to identify topics in document sets and extract key topics from the documents. Next, the identified themes are combined with the timestamps of the documents to construct time-series data of theme changes over time. The lifecycle model uses a double exponential function to fit the time-series data of a topic, revealing the complete lifecycle process of the topic from rise to decline. The double exponential function is used to describe the rapid growth during the rising stage of a topic and the gradual weakening during the declining stage. Finally, based on the fitting results, the lifecycle characteristics of the theme, such as rise time, peak time, decline time, etc., are analyzed in order to identify the reasons and significance behind these characteristics.

In this paper, building upon the thematic data extracted from the LDA model, we further identify hotspot themes, thereby revealing the future developmental directions of emerging technologies. Based on the identification results of the LDA model and drawing from existing research methodologies, we propose a dual-index theme lifecycle analysis method that combines novelty (NI, novelty index) and support (SI, strength index) mixed discriminative indicators with lifecycle stage characteristics to achieve the identification of hotspot themes [42]. Specifically, this is undertaken as follows:

(1) Theme Novelty

The novelty index measures the impact of a theme across the temporal dimension [43], assessing its novelty based on the duration of the theme's existence; specifically, a shorter duration indicates greater novelty, lesser impact, and a quicker rate of obsolescence. The novelty index evaluates a theme's newness based on its age, referencing the novelty calculation formula proposed by Wu et al. [44], as shown in Equation (3):

$$NI_t = \frac{1}{y - t_i + 1} \qquad (0 < NI < 1) \tag{3}$$

where y represents the current year and t_i is the time of the first appearance of theme i ($t \leq y$). Thus, as the duration of a theme's existence increases, its novelty diminishes, resulting in a decreasing slope in the novelty index graph. This implies that studies from emerging periods tend to dissipate more rapidly, whereas the valuable literature is often preserved as time progresses; its rate of obsolescence gradually declines, leading to a decreasing slope in the indicator graph. By observing the trends in novelty index changes, we can measure the innovativeness of technology, predict the future development direction of technology topics, and indirectly evaluate the market potential of technology. This has important reference significance for identifying emerging technologies.

(2) Theme Support

The support index gauges the attention a theme receives, revealing its impact within the intensity dimension. This is primarily represented by the volume of data related to a theme [45]. Therefore, theme support is defined as the ratio of the volume of supporting data to the total volume of data within the same timeframe, with the calculation formula provided in Equation (4). Based on this, by establishing a standard threshold, we can compare the probability distribution of various themes across different datasets, enabling us to filter the supporting data for each theme and subsequently measure its support level.

$$SI_y^d = \frac{Sum_d}{Sum_y} \tag{4}$$

where y is the current year, Sum_y denotes the total volume of data up to the current year, and Sum_d indicates the volume of supporting data up to the current year. It is evident that a higher SI indicates a greater proportion of supporting data, reflecting a higher theme support level. Therefore, the support index can reflect the level of attention given to the technology and can also serve as a reference indicator for evaluating the maturity of the technology. For developers and investors of emerging technologies, supportive indices have important guiding significance. By focusing on highly supported technology topics, market demand and technology trends can be more accurately identified, leading to the development of more rational technology research and investment strategies.

(3) Dual-Index Theme Lifecycle Analysis Method

By constructing a thematic model segmented by time period, the novelty of each theme is relatively fixed within a designated timeframe. When coupled with the corresponding support level for that time period, we can ascertain the developmental stage of the theme during a given timeframe. To illustrate the evolution of the lifecycle, we establish a two-dimensional theme lifecycle coordinate graph with the standard threshold as the origin, where novelty and support serve as the horizontal and vertical coordinates, respectively [46].

Corresponding to the stages of development, growth, maturity, and decline within lifecycle theory, we propose four distinct phases representing theme intensity in relation to the dimensions of novelty and support: the introduction phase, emerging phase, hotspot phase, and decline phase, as illustrated in Figure 3.

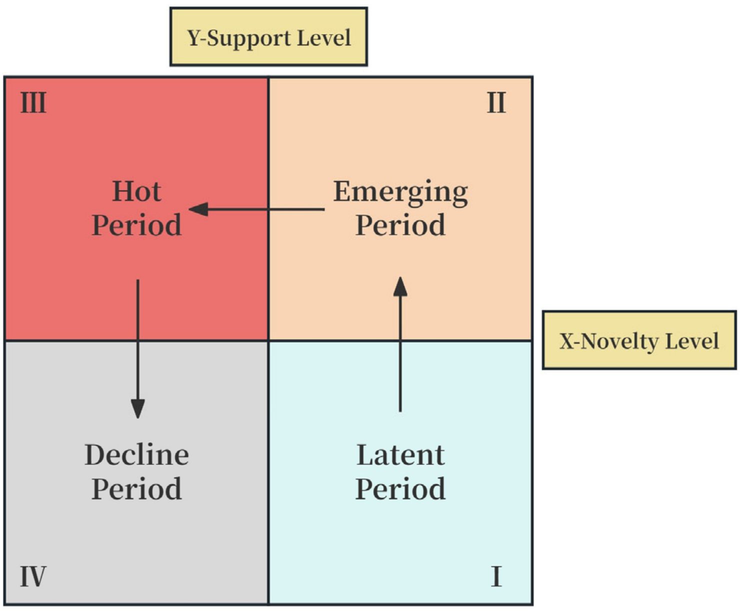

Figure 3. Dual-indicator topic lifecycle coordination diagram.

The four phases depicted in the figure are located in four distinct areas, with each theme identified via the LDA model corresponding to its respective area.

(1) Introduction phase: situated in Area I, themes during this phase typically exhibit high novelty but low support. They are characterized by a slow growth rate of supporting data, indicating that research in this field is just beginning to emerge, with related studies still being scarce;

(2) Emerging phase: located in Area II, this phase sees an increasing growth rate in terms of data volume, i.e., both the novelty and support of the theme are relatively high, suggesting that research related to the theme is developing rapidly;

(3) Hotspot phase: found in Area III, themes in this stage experience a decline in novelty but support remains high, with a stable data growth rate. This signifies that the level of development and research enthusiasm surrounding the theme is rising, placing it in a mature phase;

(4) Decline phase: positioned in Area IV, themes in this phase exhibit low novelty and minimal support, indicating that these themes have existed for a long time, with waning research enthusiasm. Themes in decline develop slowly and reach a low point, eventually being supplanted by emerging themes.

In summary, using the dual-index theme analysis method we can calculate themes that fall within Area III, the hotspot phase, and identify them as hotspot themes.

4. Empirical Research

Since its inception in 2009, blockchain technology has garnered extensive attention in both domestic and international media, initially in relation to the application of Bitcoin. In subsequent years, blockchain technology has progressively developed and spread across various facets of the global financial sector, leading to the emergence of blockchain financial technology. Through this technology, all assets can be transformed into digital assets, with registration, trading, and storage achievable via blockchain; these assets can be directly exchanged, controlled, and traded within the blockchain system [47,48]. Blockchain financial technology has begun to yield results in diverse applications across various fields, including payment settlements, banking credit reporting, the bill market, supply chain finance, insurance, and securities. This paper conducts an empirical study utilizing blockchain financial technology as a case study. We focus on theme identification and hotspot theme extraction from multiple sources of information, ultimately validating the feasibility of the proposed research method.

As one of the world's largest economies, the speed and scale of China's development in the financial sector and in the field of blockchain technology are extremely significant, with a close connection to the global market. The Chinese government has strict and comprehensive regulatory policies regarding blockchain technology. On the one hand, the government regulates the development of blockchain technology, formulating relevant regulations and policies to ensure its legality. On the other hand, the government also encourages and supports innovative applications of blockchain technology in fields such as finance. This regulatory policy not only ensures the healthy development of blockchain technology but also provides legal protection for its application in the financial field. In addition, the advanced technological infrastructure in China provides good technical support for the application of blockchain technology in the financial field. Therefore, studying data and trends in the Chinese market is of great significance for understanding the development of global blockchain finance.

4.1. Multi-Source Information Acquisition

Taking blockchain financial technology as an example, this study identifies emerging technology hotspot themes. The data employed originate from various sources, including papers, patents, books, public sentiments, and industry reports, as follows:

(1) Paper data: sourced from the China National Knowledge Infrastructure (CNKI) database. The search criterion was set to "Theme = Blockchain Finance". To ensure the

scientific accuracy of the literature, only journal articles from core journals, CSSCI journals, and CSCD journals published between 2014 and 2021 were included. A total of 1447 articles were retrieved;

(2) Patent data: also sourced from the CNKI database. The search criterion used was "Theme = Blockchain Finance", with the search scope encompassing Chinese invention patents, utility model patents, and design patents. The time frame was constrained by the publication date and set from 1 January 2014 to 31 December 2021, resulting in the retrieval of 2444 patents;

(3) Book data: sourced from the National Library catalog inquiry system. A multi-database search was conducted. The search criterion was set to "Main Title = Blockchain Finance", and both Chinese and special collections databases were searched. The search yielded 99 results;

(4) Public sentiment data: sourced from Weibo threads using the keyword "Blockchain Finance". A total of 654 posts related to this topic were retrieved from the Weibo thread;

(5) Industry reports: sourced from Chinese internet data information networks. A total of 29 publicly released reports on "Blockchain Finance" were identified.

The results from the above searches were organized, leading to the compilation of a multi-source information table on blockchain financial technology, as shown in Table 1.

Table 1. Multi-source information source table for blockchain financial technology.

Data Type	Data Source	Data Retrieval Scope	Data Count
Paper Data	CNKI Database	Core Journals, CSSCI Journals, CSCD Journals (2014–2021)	1447
Patent Data	CNKI Database	China Invention Patents, China Utility Model Patents, China Design Patents (2014–2021)	2444
Book Data	National Library Catalog Search System	Chinese and Special Collection Database, Chinese General Book Database	99
Public Opinion Data	Weibo Super Topics	Keyword "Blockchain Finance"	654
Industry Report	Chinese Internet Data Information Network	Keyword "Blockchain Finance"	29

4.2. Multi-Source Information Preprocessing

To enhance the identification of themes related to blockchain financial technology, the retrieved results were analyzed based on changing data volume trends, and the data were segmented chronologically. Blockchain finance emerged relatively recently, with low publication volumes in the early years. It was noted that following the issuance of the "Blockchain Information Service Management Regulations" by the National Internet Information Office in 2019, which encouraged the application of blockchain technology in the financial sector, the volume of related literature began to experience rapid growth. Therefore, to identify the volume of publications across different periods, the multi-source information data were divided into five segments (2014–2017, 2018, 2019, 2020, and 2021), and the following steps were undertaken for preprocessing:

(1) Data cleaning: the dataset, encompassing papers, patents, books, public sentiments, and industry reports related to blockchain financial technology, was filtered to remove duplicate or low-quality entries. Essential bibliographic information, including titles, abstracts, and keywords, was extracted and consolidated to establish a foundational corpus;

(2) Corpus establishment: keywords from the titles and abstracts were selected to form a custom dictionary, and a stopword list was created based on the characteristics of blockchain financial technology, eliminating filler words and non-significant symbols to enhance the effectiveness of word segmentation;

(3) Word segmentation: the custom dictionary and stopword list for blockchain finance were imported, and the Jieba library was employed to process the corpus for word segmentation;

(4) Keyword extraction: the "SmartAnalyze Text Big Data Analysis Research Platform" was utilized to extract features from the segmented text. This served as the input source for the LDA model.

4.3. Word Frequency Statistical Analysis

To form a preliminary understanding of blockchain financial technology, a word frequency statistical analysis was conducted before the thematic analysis, focusing on high-frequency terms. Given that paper and patent data represented the majority of the multi-source information dataset, the word frequency analysis was performed using 1447 paper entries and 2444 patent entries. The data sources for papers included titles, abstracts, and keywords, while for patents, the sources comprised titles, independent claims, and keywords. After removing filler and non-significant words, the top 20 most frequently occurring terms for both papers and patents were identified, as shown in Tables 2 and 3.

Table 2. Paper data word frequency statistics table (top 20).

Rank	Label Word	Frequency	Rank	Label Word	Frequency
1	Blockchain	8438	11	Technology	836
2	Technology	4915	12	Intelligent	831
3	Finance	2489	13	Model	822
4	Regulation	1426	14	Risk	812
5	Data	1399	15	Mechanism	798
6	Digital	1342	16	Transaction	766
7	Currency	1190	17	Contract	721
8	Information	1042	18	Internet	646
9	Innovation	937	19	Economy	645
10	Supply Chain	893	20	Decentralization	550

Table 3. Patent data word frequency statistics table (top 20).

Rank	Label Word	Frequency	Rank	Label Word	Frequency
1	Blockchain	21762	11	Storage	3272
2	Data	17478	12	Intelligent	2863
3	Information	13140	13	Management	2853
4	Transaction	10748	14	Payment	2507
5	System	6187	15	Service	2096
6	Business	5549	16	Encryption	2048
7	Finance	4176	17	Consensus	2008
8	Network	3826	18	Digital	1869
9	Contract	3493	19	Financing	1404
10	Assets	3344	20	Supply Chain	1055

As indicated in Tables 2 and 3, terms such as "blockchain", "data", "finance", and "information" appear with high frequency, along with related terms like "digital," "currency", and "network", which also exhibit relatively high occurrence rates. This suggests that blockchain financial technology has garnered significant attention in areas such as fintech and digital currency, leading to the inference that its hotspot themes are likely concentrated in these related fields.

4.4. Theme Identification Based on Multi-Source Information

Theme identification was conducted using the LDA library of the scikit-learn machine learning toolkit in Python [49]. A critical step in this process is determining the optimal number of topics, which involves identifying the most suitable quantity of latent themes from the document dataset. The optimal number of themes for different time periods is established based on perplexity; typically, when the trend in the perplexity change curve exhibits minimal decline or reaches an inflection point, the corresponding optimal number of themes is attained. Following the methodology outlined in Wang Qian et al. [50], we set the prior parameters $\alpha = 50/K$ and $\beta = 0.01$, where K is the number of latent topics, and established an iteration count of $I = 100$. The model demonstrated satisfactory convergence, as detailed in Table 4.

Table 4. Main parameters and their values.

Parameter	Parameter Meaning	Value
α	Prior distribution parameter for topic distribution θ	$50/K$
β	Prior distribution parameter for topic-word distribution φ	0.01
I	The maximum number of iterations allowed for LDA convergence	100
K	Number of latent topics	-

Based on the aforementioned settings, the perplexity change curves for different numbers of topics across the five time periods from 2014 to 2021 were obtained (see Figure 4). Observing the model's performance at varying values of K, it is evident that when the number of topics is set to 6, 10, 14, 19, or 22, the perplexity experiences inflection points at different time periods, after which the rate of decline slows. Therefore, it was determined that the optimal number of themes for blockchain financial technology from 2014 to 2017 was 6, while the optimal numbers for the years 2018, 2019, 2020, and 2021 were 10, 14, 19, and 22, respectively.

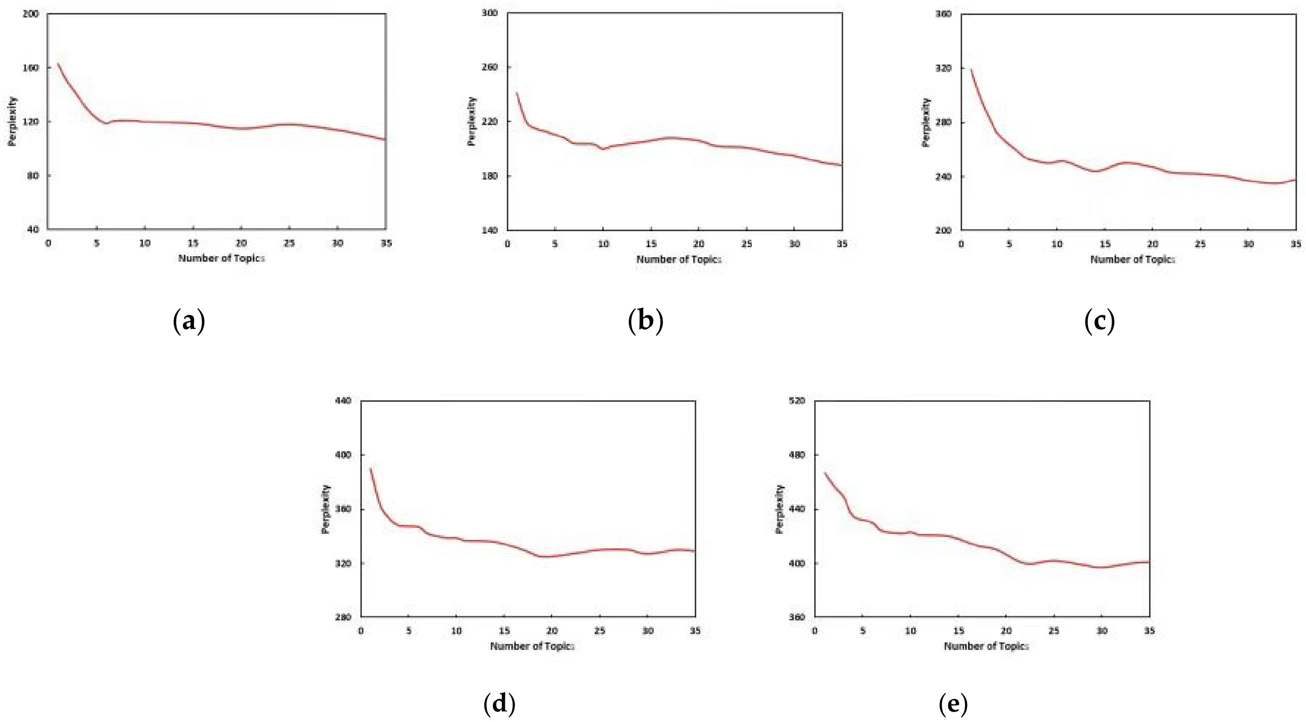

Figure 4. Perplexity variation curves for different number of topics from 2014 to 2021. (**a**) Perplexity variation curves for different number of topics from 2014 to 2017. (**b**) Perplexity variation curves for different numbers of topics in 2018. (**c**) Perplexity variation curves for different numbers of topics in 2019. (**d**) Perplexity variation curves for different number of topics in 2020. (**e**) Perplexity variation curves for different numbers of topics in 2021.

Using LDA to perform text mining on the preprocessed multi-source information data, the corresponding topic words were generated. Subsequently, theme output for each time period was filtered to remove theme clusters that were unrelated to or had minimal relevance to blockchain financial technology research, clusters composed solely of filler words, and themes with a data volume of zero [51,52]. The filtered results were then assigned thematic labels. To ensure the precise retention of theme semantics, the thematic labels were referenced against the Chinese Library Classification System, the results of which are presented in Table 5.

Table 5. Distribution of blockchain financial technology topics in different time periods.

Time Period	Number of Topics	Mining Results
2014–2017	6	Topic1: Decentralization; Topic2: Digital Currency; Topic3: Mobile Payment; Topic4: Online Credit; Topic5: Securities Trading; Topic6: Supply Chain Finance
2018	10	Topic1: Artificial Intelligence; Topic2: Audit; Topic3: Decentralization; Topic4: Supply Chain Finance; Topic5: Cross-border Payment; Topic6: Insurance Management; Topic7: Financial Technology; Topic8: Digital Bills; Topic9: Digital Currency; Topic10: Securities Trading
2019	14	Topic1: Audit; Topic2: Securities Trading; Topic3: Financial Technology; Topic4: Cross-border Payment; Topic5: Artificial Intelligence; Topic6: Data Provenance; Topic7: Data Security; Topic8: Insurance Management; Topic9: Digital Currency; Topic10: Decentralization; Topic11: Digital Bills; Topic12: Library and Archives Management; Topic13: Supply Chain Finance; Topic14: Consensus Mechanism
2020	19	Topic1: Insurance Management; Topic2: Decentralization; Topic3: Digital Bills; Topic4: Taxation; Topic5: Identity Authentication; Topic6: Library and Archives Management; Topic7: Supply Chain Finance; Topic8: Machine Learning; Topic9: Social Governance; Topic10: Financial Credit Reporting; Topic11: Mobile Payment; Topic12: Consensus Mechanism; Topic13: Public Trust; Topic14: Financial Technology; Topic15: Digital Currency; Topic16: Audit; Topic17: Securities Trading; Topic18: Inclusive Finance; Topic19: Cross-border Payment
2021	22	Topic1: Decentralization; Topic2: Cross-border Payment; Topic3: Digital Currency; Topic4: Digital Bills; Topic5: Taxation; Topic6: Library and Archives Management; Topic7: Machine Learning; Topic8: Social Governance; Topic9: Insurance Management; Topic10: Data Security; Topic11: Financial Credit Reporting; Topic12: Public Trust; Topic13: Mobile Payment; Topic14: Consensus Mechanism; Topic15: Smart Contracts; Topic16: Supply Chain Finance; Topic17: Financial Technology; Topic18: Audit; Topic19: Securities Trading; Topic20: Inclusive Finance; Topic21: Contract Security and Identity Authentication; Topic22: Loan Trading

4.5. Hot Topic Extraction

Based on the thematic information identified via the LDA topic model, hotspot themes were extracted by calculating the novelty and support of each theme using the dual-index theme lifecycle analysis method. The novelty for each theme was computed according to Equation (3), with the average novelty of all themes serving as the standard threshold. The calculations yielded a standard threshold for the novelty index of 6.14%. Using the same method, the standard threshold for the support index, calculated according to Equation (4), was found to be 3.79%. According to the theme lifecycle coordinate graph, the themes that met the criteria of having a novelty value lower than the standard threshold and a support value greater than the standard threshold were classified as hotspot themes. Ultimately, the extracted hotspot themes related to blockchain financial technology were fintech, cross-border payments, digital invoices, supply chain finance, decentralization, mobile payments, securities trading, and insurance management, totaling eight themes, as illustrated in Figure 5.

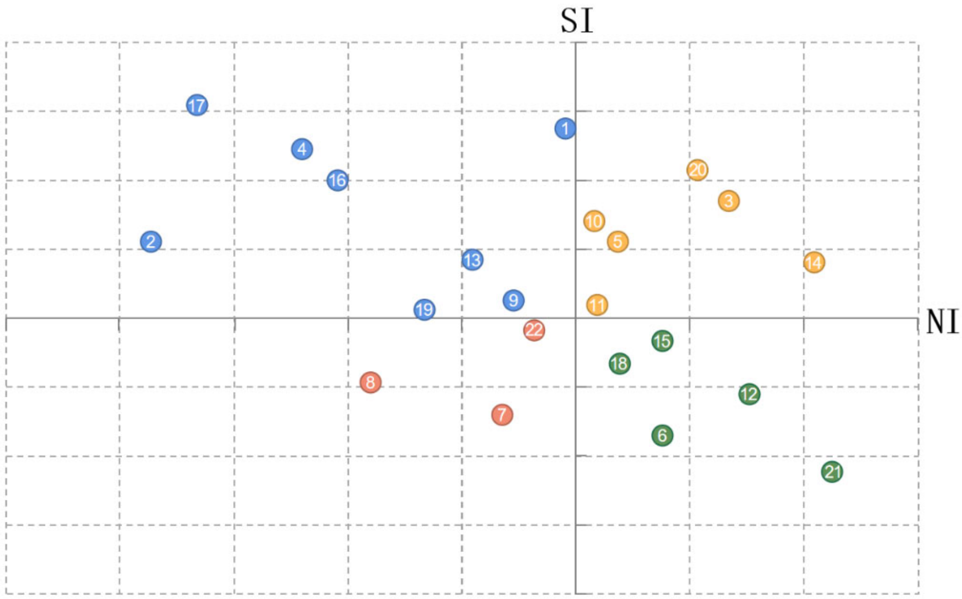

Figure 5. Distribution map of hot topics in blockchain financial technology.

4.6. Validity Analysis

To verify the accuracy and comprehensiveness of the identification results, this article uses an expert verification method to analyze the effectiveness of this approach in identifying the hot topics related to blockchain finance.

Firstly, we designed a survey questionnaire based on the preliminary blockchain finance technology themes (Table 5) and set quantitative options such as importance, attention, and innovation for all themes, as well as open-ended questions for experts to select, evaluate, and supplement. Secondly, 50 experts from financial institutions, blockchain technology companies, relevant academic fields, and government or regulatory agencies were invited to fill out the survey questionnaires. In total, 47 valid questionnaires were collected. We conducted statistical analysis on the questionnaire results, analyzed the consistency of (and differences in) expert opinions, identified potential points of controversy and consensus, and ultimately established consensus through multiple rounds of consultation. Finally, based on the comprehensive evaluation results, the hot topics in the field of blockchain finance were identified. These were basically consistent with the results obtained from the LDA topic model and dual-index theme lifecycle analysis method.

4.7. Results Analysis

The research identified the hotspot themes of blockchain financial technology as follows: fintech, cross-border payments, digital invoices, supply chain finance, decentralization, mobile payments, securities trading, and insurance management. Furthermore, the hotspot distribution graph revealed that, among the eight hotspot themes, topic 2 (cross-border payments), topic 4 (digital invoices), topic 16 (supply chain finance), and topic 17 (fintech) exhibited significantly higher intensity than topic 1 (decentralization), topic 9 (insurance management), topic 13 (mobile payments), and topic 19 (securities trading). While “decentralization” had a high support level, its novelty was also relatively high, placing it near the SI standard threshold. “Insurance management,” “mobile payments,” and “securities trading” showed no significant advantages in either novelty or support and thus were clustered near the origin of the standard threshold. In contrast, “fintech,” “cross-border payments,” “digital invoices,” and “supply chain finance” were situated in the upper-left region of the overall theme distribution graph, clearly displaying the characteristics of hotspot themes. The following sections provide an interpretation of the four themes with the highest intensity.

4.7.1. Topic 17: Fintech

In traditional finance, financial activities are usually limited to three main services: deposits, loans, and settlements. All of these heavily rely on physical branches, resulting in poor user experience, high labor costs, excessive labor demand, and increased barriers to entry into the industry. The integration of finance and technology is a key driving force of transformation, pushing forward industrial development. For example, "Big Data + Blockchain Credit Reporting" enhances credit reporting through big data, promoting a wider range of services, larger data volumes, more refined data sources, more analytical methods, and faster processing speeds, ultimately creating objective and effective credit reports for financial institutions. As time has passed, financial technology has gradually transformed from a single technological application to a comprehensive solution—a multi-technology fusion ecosystem comprising blockchain, artificial intelligence, big data, cloud computing, etc. This evolution not only promotes the intelligent, automated, and personalized development of financial services but also promotes the deep integration of finance with the real economy and society, injecting new vitality into economic development.

4.7.2. Topic 4: Digital Invoices

In traditional invoice systems, the process of issuing, circulating, reimbursing, and redeeming invoices is complex and difficult to control, and there is a lack of unified verification mechanisms between multiple entities. Problems include sales of paper invoices, a lack of synchronization, and failure to endorse electronic invoices for payment. As time has passed, the evolution of digital invoices has become increasingly profound. Despite the advantages of traditional invoices, digital invoices are a more secure, intelligent, and convenient invoice form, utilizing the advantages of blockchain finance, promoting the standardization and transparency of the invoice market, and effectively reducing the risks of the invoice market. In addition, the popularization of digital invoices has achieved seamless integration across platforms and regions, which not only reduces the development and maintenance costs related to central servers but also solves the synchronization problem in invoice registration caused by centralization. Digital invoices are more suitable for the development of the digital economy.

4.7.3. Topic 2: Cross-Border Payments

For a long time, international trade transactions and payment settlements have relied on the banking system. This traditional transaction method conducted through banks involves multiple organizations, each with its own accounting system, resulting in cumbersome processing workflows and requiring the establishment of agency relationships to complete transactions. With the continuous development of blockchain financial technology, its advantages in the field of cross-border payments are becoming increasingly apparent. Under peer-to-peer support, all nodes share a ledger and use consensus algorithms to confirm peer-to-peer transactions between nodes, transmitting the results to all nodes and achieving collaborative governance. This enables cross-border enterprises to make direct transfers, significantly improving the efficiency of cross-border payments. This also makes cross-border transactions traceable, providing effective regulatory tools for regulatory agencies. With the growing maturity and popularization of blockchain technology, cross-border payments will become more efficient and secure, contributing to the prosperity and development of the global economy.

4.7.4. Topic 6: Supply Chain Finance

In the traditional financial intermediary model, challenges such as information asymmetry, evaluating repayment ability, transaction authenticity, scattered and difficult-to-share information, and uncontrolled performance risks plague supply chain financing. The emergence of blockchain financial technology has effectively promoted the disintermediation of the financial sector, shortened the chain from public consumption surplus to enterprise expansion, stimulated the supply and demand of direct financing in the capital market, and significantly improved the efficiency of capital circulation and allocation, thereby reducing capital surplus. In addition, blockchain finance technology solves trust problems through consensus algorithms; reduces performance risks through smart contracts; connects the flow of goods, logistics, capital, and information in the supply chain; and tracks the operational status of enterprises in the supply chain in real time. With the growing maturity of technology and the continuous expansion of application scenarios, supply chain finance is gradually building an ecosystem that integrates optimal flow, logistics information, capital integration, and data sharing.

5. Conclusions

This paper utilizes blockchain financial technology as a case study, integrating five types of information—papers, patents, books, public sentiments, and industry reports—to identify themes related to this emerging technology using the LDA topic model. Additionally, we employed the dual-index theme lifecycle analysis method to extract hotspot themes, providing insights into the developmental direction of emerging technologies through the interpretation of these themes. Comprehensively revealing the various characteristics of blockchain financial technology from a diverse information perspective and establishing a firm understanding of the multidimensional aspects of blockchain financial technology can help us identify the complex applications and potential impacts of blockchain technology in the financial field. In addition, this also promotes its application and popularization in other fields, thereby accelerating the digital transformation and innovative development of the financial industry. The application of the aforementioned models ultimately identified 22 themes associated with blockchain financial technology (as of 2021), from which 8 hotspot themes were extracted, including fintech, cross-border payments, digital invoices, supply chain finance, and decentralization. These hot topics not only reflect the current focus of blockchain technology but also foreshadow future development trends. This has important reference value for policymakers, financial institutions, and technology companies: policymakers can adjust regulatory policies based on the trends revealed by research, financial institutions can clarify the direction of technological innovation, and technology companies can discover new market opportunities.

This study identifies emerging technology hotspots using multi-source information, avoiding the biases and limitations that can arise from single-source data. It not only enriches the dimensions of the data but also enhances the comprehensiveness and accuracy of the analysis results through cross-validation, accurately identifying the hotspots and trends in emerging technologies. Moreover, due to the real-time and extensive nature of multi-source information, this research method can also capture technological trends in a timely manner, predict future development directions, enhance the timeliness and foresight of research, and provide scientific and comprehensive bases for policy formulation and decision support, which is of great significance. This study also provides research ideas for other scholars and researchers and contributes to promoting theoretical innovation and practical development in the field of technology prediction and evaluation.

However, the research has certain limitations. Firstly, in the selection of multi-source data, only five widely influential sources were considered, leaving room for the further enrichment of data sources for deeper exploration; secondly, during the data cleaning process, we only extracted the titles, abstracts, and keywords from the bibliographic information of the literature, without designing specialized extraction strategies for different types of data. As a result, the representativeness of the data may be affected, necessitating the further optimization of the data preprocessing approach to enhance the effectiveness of theme identification.

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