

Article

A Novel Method for Technology Roadmapping: Nanorobots

Huailan Liu ¹, Zhen Li ^{2,3,*} , Rui Zhang ^{1,*} , Yufei Liu ⁴ and Yixin He ^{1,5}

¹ School of Mechanical Science and Engineering, Huazhong University of Science and Technology, Wuhan 430074, China; lhlan@hust.edu.cn (H.L.); m202270567@hust.edu.cn (Y.H.)

² School of Public Administration, Zhongnan University of Economics and Law, Wuhan 430073, China

³ National Research Laboratory for Smart Social Governance (Elderly Care), Zhongnan University of Economics and Law, Wuhan 430073, China

⁴ Center for Strategic Studies, Chinese Academy of Engineering, Beijing 100088, China; liuyf@cae.cn

⁵ National Center of Technology Innovation for Intelligent Design and Numerical Control, Huazhong University of Science and Technology, Wuhan 430074, China

* Correspondence: zhenli_jane@foxmail.com (Z.L.); m202077005@alumni.hust.edu.cn (R.Z.)

Abstract: In the dynamic field of robotics engineering, nanorobot technology has witnessed rapid advancements. Developing a technology roadmap is essential for quickly identifying the trends and key technological aspects of nanorobotics from an array of multi-source data. Traditional research methods, such as Delphi surveys, bibliometrics, patent analysis, and patent paper citation analyses, often fail to capture the rich semantic information available. Moreover, these approaches generally provide a unidimensional perspective, which restricts their capacity to depict the complex nature of technological evolution. To overcome these shortcomings, this paper introduces a novel framework that utilizes the ALBERT method combined with multi-source data for critical theme extraction. It integrates varied data sources, including academic papers and patents, to explore the interrelation within the nanorobot technology roadmap. The methodology begins with text feature extraction, clustering algorithms, and theme mining to identify dominant technological themes. Subsequently, it applies semantic similarity measures to connect multiple themes, employing a “multi-layer ThemeRiver map” for a visual representation of these inter-layer connections. The paper concludes with a comprehensive analysis from both the technological research and industrial application perspectives, underscoring the principal developmental themes and insights of nanorobot technology, and projecting its future directions.



Citation: Liu, H.; Li, Z.; Zhang, R.; Liu, Y.; He, Y. A Novel Method for Technology Roadmapping: Nanorobots. *Appl. Sci.* **2024**, *14*, 10606. <https://doi.org/10.3390/app142210606>

Academic Editor: Luis Javier Garcia Villalba

Received: 30 August 2024

Revised: 18 October 2024

Accepted: 12 November 2024

Published: 18 November 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

Keywords: technology roadmapping; multi-source data; nanorobots; text feature mining; theme mining; ThemeRiver map

1. Introduction

In recent years, emerging technologies such as artificial intelligence, information technology, medical technology, and nanotechnology have continuously transformed existing industries [1]. The development of nanomaterials has particularly catalyzed in-depth research into nanorobot technology, emphasizing materials, structures, and control methods [2–5]. This research has been further enhanced by the innovative applications of big data and artificial intelligence, which are becoming fundamental to the advancement of nanorobot technology [6,7]. In this context, nanomaterials act as the critical building blocks for the creation of sophisticated nanorobots, effectively bridging the gap between material science and robotics. However, the innovation and development of nanorobot technology have encountered significant challenges. Firstly, the knowledge base of nanotechnology is progressively expanding and becoming more specialized. The field of nanorobotics is experiencing significant convergence with other subfields, making it challenging to define a clear technological roadmap [8]. Zhou et al. compared the knowledge bases of wind turbine firms, emphasizing the importance of a broad and deep knowledge base for technological advancement [9]. Similarly, the complex architecture of nanorobots requires a

comprehensive understanding that spans across various technological domains. This interdisciplinary nature, involving engineering, life sciences, and medicine, presents challenges in developing fully functional nanorobots for critical applications such as cancer therapy, site-specific drug delivery, and advanced surgery [10]. The absence of novel methods to detect and specify abrupt changes in technological, market, and institutional dimensions has been a limiting factor in the field's progression [11]. Notably, interdisciplinary integration is essential in identifying and fostering emerging technological fields. Kong et al. underscore that the convergence of knowledge across disciplines is crucial for the early identification of emerging technologies. By tracking citation networks between different scientific fields and applying machine learning techniques such as topology clustering and network visualization, their study illustrates how knowledge flow between disciplines fosters new areas of innovation. This process-based approach emphasizes the dynamic nature of technological emergence, highlighting the importance of integrating knowledge from diverse fields to develop novel technologies [1]. Interdisciplinary integration is not only a pathway to technological convergence, but is also a critical method for detecting the early formation of emerging technologies across various domains. Secondly, the rapid development in nanorobot technology is driven by continual breakthroughs in nanotechnology, generating a vast amount of diverse technological and application data at different levels. This demands iterative innovations in data analysis and application methods, particularly for big data applications, which involves integrating techniques from artificial intelligence, nanotechnology, and embedded smart sensors to address complex challenges in medical procedures, early disease diagnoses, and patient monitoring [12]. Thus, outlining the development trajectory of nanorobot technology, understanding its technological evolution patterns, and constructing a technology roadmap with the interrelations across various thematic dimensions are of significant practical importance.

Technology roadmaps were originally applied in the automotive industry, where related companies utilized them to reduce manufacturing costs. In the 1980s, Motorola and Corning employed technology roadmaps for corporate management and enterprise development planning. Various scholars have conducted in-depth research on technology roadmaps, including Professor Phaal from the UK, who proposed roadmap drawing methods such as T-Plan [13] and S-Plan. Traditional technology roadmap development methods have favored Delphi surveys, relying on expert knowledge to identify technological, industrial, and product themes. They often encounter difficulties in analyzing the semantic content within technological texts. Some scholars have sought to enhance expert interactions with objective data, but they have often used a unidimensional data analysis to track technological evolution trends. Technological development is diverse, and the semantic information in multi-source text data contains more hidden information that is challenging to identify, such as how technology drives product development and how the market propels technological advancements. Analyzing the evolution of themes from a multi-dimensional perspective can provide a more comprehensive understanding of the direction of technological development in a field and enhance the quality of technology roadmaps.

In the context of a multi-dimensional perspective topic analysis, the selection of an appropriate model is critical due to the need to handle diverse datasets and facilitate a detailed topic extraction and analysis. ALBERT, short for A Lite BERT and developed by Google in 2019, represents an advanced version of BERT that mitigates issues related to a large parameter size and a high computational demand. ALBERT introduces cross-layer parameter sharing and factorized embedding parameterization, which significantly reduce the model's parameter count, thereby enabling the processing of larger datasets within constrained computational limits [14]. These modifications not only enhance the efficiency of the model, but they also improve its regularization, leading to better generalization across tasks. This is particularly advantageous for analyzing multi-topic texts, especially in applications involving diverse and cross-domain textual datasets [15]. When compared to other models, such as the RoBERTa, DistilBERT, and GPT models, the ALBERT model

stands out for its lightweight architecture and superior performance in the granularity of topic analyses. Consequently, the ALBERT model is selected for its robust performance in the analysis of multi-thematic texts.

Regulatory, ethical, and safety issues associated with deploying nanorobots and technology roadmapping should be considered thoroughly in practice in the first place. This paper focuses on the technological developments of nanorobots using a novel technology roadmapping method. It introduces an innovative framework that utilizes the ALBERT method to refine and interpret nanorobot technology themes, thereby enhancing the understanding and strategic planning within this domain [16]. It employs text information mining and presents a nanorobot technology roadmap interrelation analysis framework based on the ALBERT method. This approach improves traditional technology roadmap construction methods in two ways: firstly, this paper utilizes automated phrase mining to refine key themes, substantially enhancing the depth of information extraction and the interpretability of nanorobot information, and thereby improving the efficiency and accuracy of technology roadmap analyses. Secondly, this paper examines interrelations in the nanorobot technology roadmap from multiple text information sources and depicts them more effectively using the ThemeRiver map method. As a result, this approach highlights the current development focus of nanorobot technology and predicts future technological application prospects.

2. Materials and Methods

2.1. Literature Review

2.1.1. Significance of Nanorobots

The concept of nanorobots is traceable to Richard Feynman's groundbreaking 1959 lecture "There's Plenty of Room at the Bottom", in which he envisioned the possibility of manipulating matter at the molecular or atomic scale [17]. This pioneering concept not only laid the foundation for nanotechnology, but also heralded the emergence of nanorobots. Feynman's vision extended beyond mere miniaturization; it encapsulated the precise manipulation of matter at its most fundamental level, foreseeing a future where both manufacturing and medical interventions could be conducted on atomic or molecular scales [17].

The significance of nanorobots has evolved substantially from Feynman's initial vision, growing into a multidisciplinary field that encompasses physics, chemistry, biology, and engineering. This interdisciplinary expansion is evidenced by the work of Qiu and Nelson [18], who have explored the biomedical applications of magnetic helical micro-/nanorobots, highlighting their potential for minimally invasive surgery and targeted therapy. Nanorobots enable direct observation [19–21], functional assessments [22–24], and manipulation [25–27] on the atomic, molecular, and nanoscale levels, greatly enhancing our understanding of nanoscale science. Recent advancements in nanorobotics have demonstrated potential applications in targeted drug delivery, precision surgery, and environmental remediation. For instance, nanorobots could be designed to navigate through bodily fluids to deliver drugs with a high precision, minimizing the side effects and improving the therapeutic efficacy [2]. Zhang et al. [28] contributed to this field by exploring the rational design of microalgae-based biohybrid materials, which integrate the photosynthetic capabilities of microalgae with biocompatible materials for diverse biomedical applications.

The architecture of nanorobots encompasses an array of components, including very-large-scale integration (VLSI) and nanoelectronic circuits, chemical and temperature sensors, actuators, power supplies, and data transmission devices. For instance, Miao et al. [29] took inspiration from the flagellar/ciliary intrinsic driven mechanism to develop an all-in-one tubular robotic actuator, showcasing the potential for the use of a biomimetic design in microrobotic systems. Lin et al. conducted a moderated mediating examination of intermediaries' effects on corporate innovation, which could be relevant for understanding the complex architecture of nanorobots and its impact on technological innovation [30]. The advent of emerging technologies in artificial intelligence, electronic information, and

advanced materials has propelled nanorobotics forward, yielding significant research breakthroughs in biomedical applications, defense, environmental conservation, and industrial manufacturing. Despite these advancements, the practical deployment of nanorobots faces myriad challenges [31–39] due to their nanoscale dimensions, which complicates the integration of multiple functionalities into a single unit. In biomimetic nanorobotics, preserving the biological activity while ensuring sensing accuracy remains difficult. Additionally, a single nanorobot can typically perform only one task, making the synchronization and coordination of multiple nanorobots for various tasks a theme worthy of exploration. Therefore, understanding the development trajectory and future trends of nanorobot technology requires thorough analysis and careful study.

2.1.2. Current Technology Roadmapping Method

A technology roadmap can be viewed as a structured framework based on the dimension of time, and can be used for managing innovation strategies through layered thematic representations [40]. It explores the evolutionary relationships among technology, markets, and products, effectively aligning technological advancements with business objectives [41]. The structure of “layers” and “sub-layers” is crucial because it reflects the fundamental direction in which an organization addresses business issues. It facilitates communication between different business departments and integrates key business processes [42]. This layered structure is instrumental in fostering communication across various business departments and in the integration of essential business processes, thereby enhancing strategic coherence and operational efficiency [41].

Currently, there are three main methods for developing technology roadmaps: qualitative analyses, bibliometric analyses, and intelligent analyses. A qualitative analysis is the most widely applied method for creating technology roadmaps. Many scholars support and validate technology roadmap frameworks through qualitative case studies. Some scholars develop roadmaps through workshops, incorporating qualitative knowledge from various experts and continuously iterating the roadmap development process [43–45]. A bibliometric analysis, on the other hand, involves quantitatively parsing textual data to identify thematic elements in a field. It uses data metrics to identify the direction of technological research, further supporting the development of technology roadmaps through methods like network analyses and text mining [46–48]. For instance, Wang et al. presented a pioneering approach that combines bibliometrics with a patent analysis to understand the technological trends and future directions of nanogenerators. By drawing data from the Web of Science and the Derwent World Patents Index, this study visualized the existing technological trajectory and identified key factors influencing the growth of the nanogenerator industry. The authors highlighted how bibliometric and patent analyses serve as effective tools for tracking the development of new technologies and predicting their future applications [47]. Similarly, Liu et al. introduced a novel framework for unveiling the evolutionary path of nanogenerator technology, emphasizing the use of multi-source data. Their methodology involves integrating bibliometrics and a patent citation analysis using sources like the Web of Science and the Derwent Innovation. This allows for a comprehensive exploration of both scientific and technological advancements. Their study particularly underscores the importance of text vectorization and clustering techniques in extracting thematic trends from large datasets, thereby enhancing the depth of bibliometric analyses [49]. Further expanding the scope of data sources, Liu et al. proposed an advanced framework based on multi-source data to monitor the technology evolution pathways of nanogenerators. Their study incorporated data from academic papers, patents, and grants, sourced from the Web of Science, the Derwent Innovation Index, and the China Knowledge Centre for Engineering Science and Technology. The combination of these data sources offered a more detailed view of the progression from initial research (grants and papers) to technological applications (patents). This multi-source approach is critical for identifying the knowledge flow between academic research and technological innovation [50]. The traditional technology roadmapping method has been critiqued for its limitations, particu-

larly in its ability to address complex, multifaceted systems, where the interdependencies and interactions across different technological layers are crucial. A significant drawback of conventional roadmaps is their typically linear and siloed approach, which often fails to effectively capture the dynamic interrelations and feedback loops that exist between various technologies and sectors [42]. This can result in an oversimplification of technological evolution and interdependencies, potentially leading to strategic misalignments and inefficiencies in resource allocation [51]. Therefore, this paper emphasizes the interrelation research among the different layers of the technology map.

In the era of big data, acquiring technology roadmap data has become easier. Consequently, some scholars have considered using machine learning and intelligent analysis methods to extract deeper knowledge from these technology roadmaps. Some researchers have used text mining to extract keywords from technology roadmap data and combine semantic analyses to uncover deeper insights from the data [52–55]. However, mining from a single data source may not reflect the full picture of technological development. In technology roadmap research, utilizing multiple data sources allows for a comprehensive analysis of the current state and future trends in a field from various perspectives. The interrelation between multidimensional data sources also enables the extraction of deeper semantic information [56,57].

2.1.3. Representation of Multi-Dimensional Information

In the process of developing a technology roadmap for nanorobotics, expert interaction is an indispensable and crucial step. During this stage, two core issues need to be addressed: first, how to extract information from multiple sources of text, and second, how to effectively present the collected textual information to experts so that they can efficiently and clearly understand the objective data.

With the advent of the big data era, an increasing number of scholars are focusing on the use and mining of heterogeneous data from multiple sources. Text information extraction has become a research hotspot in the field of big data analyses. One of the earliest methods used for text information extraction was keyword extraction, based on the word frequency in textual information. Later, more complex methods were proposed, such as TF-IDF and TextRank. An efficient means of understanding textual data is through the use of theme modeling, which is an important method in current research for text information extraction. To enable a computer to recognize and compute text data for extraction, text data needs to be transformed into multi-dimensional vectors and analyzed in vector space. However, a Chinese document may result in a vector space with tens of thousands of dimensions, which can be challenging to analyze. Theme models can address this issue by transforming high-dimensional vectors into low-dimensional ones while ensuring the quality of information, making them suitable for subsequent analyses. This is analogous to the approach taken by Kong et al., where a support vector machine-based classifier was used to single out high-quality patents for each innovation attribute, thus providing a more nuanced and accurate reflection of technological innovation [58].

2.1.4. A Multi-Layered ThemeRiver Model

Using the aforementioned theme modeling methods, it is possible to efficiently parse multi-source text information and extract multidimensional data representing how themes change over time. Themes at different time intervals can split or merge over time, and these processes can be visualized using a ThemeRiver model. Also, inter-layer associations in the technology roadmap are best presented using a “ThemeRiver map” to visualize. The concept of a ThemeRiver map originates from their application in visualizing the evolution of textual data. The methods for achieving this include ThemeRiver and TextFlow, with TextFlow being an extension of ThemeRiver. TextFlow not only depicts how themes change over time, but also how themes split and merge with time. For instance, a theme may split into two at a certain point in time, or multiple themes may merge into one. This visualization aids researchers in intuitively analyzing the patterns of evolution among

themes. In recent years, researchers have enhanced ThemeRiver maps for use in theme association and technology evolution analyses. The ThemeRiver model was firstly introduced by Susan Havre and Memberai in 2002 and describes the evolution of themes in a large number of documents over time in the form of a river, allowing domain experts to clearly identify trends in theme evolution and compare the relationships between themes [59]. A ThemeRiver map represents an innovative variation of stacked area charts, specifically designed to illustrate the evolution of themes or events over time. By employing a fluid, river-like form, a ThemeRiver map adeptly conveys the temporal changes in different categories of data, making them particularly adept at showcasing trends and shifts in various values over a specified period [59]. Despite their advantages in data representation, a ThemeRiver map poses certain challenges in practice, such as accurately interpreting the relationship between changes in the stream width and the actual data volumes, and managing densely packed data regions to avoid visual clutter [60]. Some scholars have made improvements to the original river model, combining it with specific subfields to expand the information dimension of the river model [49,61–67].

The concept of a multi-layered ThemeRiver map, as proposed in this text, aims to extend beyond the capabilities of a single-layer ThemeRiver map by not only depicting the temporal evolution, integration, and division of themes within individual layers, but also expressing the interconnections between different layers. This approach necessitates the application of topic identification and topic similarity computation techniques to analyze and combine themes across layers, ultimately representing them within a single comprehensive visualization. In the realm of data visualization, the integration of multiple layers into a ThemeRiver map introduces a more complex and nuanced representation of data, enabling a deeper understanding of the intricate relationships between various thematic layers over time. By employing topic identification techniques, each layer's primary themes are discerned, ensuring that the most relevant and significant themes are highlighted within the visualization [68]. Subsequently, topic similarity measures, such as the cosine similarity or the Jaccard index, are used to quantify the degree of similarity between themes across different layers [69]. This quantitative analysis facilitates the coherent integration of themes, allowing for a layered, yet interconnected, representation that encapsulates both the intra-layer and the inter-layer dynamics.

In conclusion, a multi-layered ThemeRiver map represents a significant advancement in data visualization techniques, offering a more intricate and interconnected portrayal of thematic data over time.

2.2. Methodology

In this study, we focused on text information mining from multiple sources, encompassing both research papers and patents in the field of nanorobotics. We introduced an innovative approach to theme modeling, designed to facilitate the integrative analysis of multi-source data [70]. Our method, termed AKY (incorporating the ALBERT, K-Medoids, and YAKE techniques), aims to conduct a domain analysis from the perspectives of both technological development and product applications. The overarching objective was to identify the principal areas of advancement and forecast future trends in nanorobotics by exploring the interrelation of the nanorobot technology roadmap. The methodology employed in our study is depicted in Figure 1.

There are four main steps in the process. Initially, Section 2.2.1 delves into data acquisition and preprocessing, elucidating the origins of the data and specific parameters like the range of years considered. Section 2.2.2 presents an enhanced theme modeling technique that employs the ALBERT model alongside text mining strategies, further decomposed into three principal stages. Next, evolutionary trajectories were identified using the temporal theme association analysis in Section 2.2.3. Lastly, inter-layer associations in the technology roadmap were explored, and a visualization tailored for multi-dimensional data evolution was introduced in Section 2.2.4, employing the D3.js-based ThemeRiver framework to represent thematic trajectories and interrelations over time.

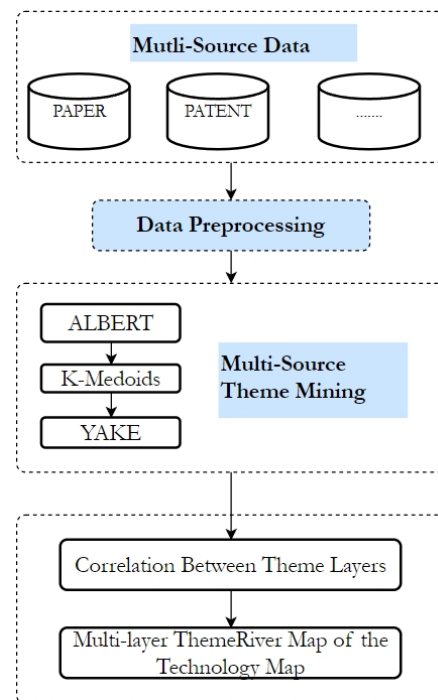


Figure 1. Methods and Procedures.

2.2.1. Data Acquisition and Preprocessing

In this research, both paper and patent data were utilized, following the approach of previous studies that have effectively drawn from sources such as the Web of Science and the Derwent Innovation Index to analyze technological trends and advancements [47,49,50]. Firstly, we selected the Web of Science (WOS) database from Thomson Reuters and established a retrieval strategy for paper searches based on keywords in the field of nanorobotics. The paper data were restricted to the years from 2003 to 2022, and included information such as paper titles, citations, abstracts, and more. Subsequently, our patent data were sourced from the Derwent Innovation Index (DII) and the Derwent Innovation (DI) platform. A patent retrieval query was devised using keywords and relevant classification codes for the nanorobotics domain, with the retrieval year range also set from 2003 to 2022. These data included patent names, citation information, timestamps, and abstracts. In the end, we retrieved a total of 21,363 papers and 26,711 patents.

2.2.2. Enhanced Theme Modeling Method by Employing ALBERT and Text Mining Techniques

In this paper, the theme modeling of multi-source text data comprised three steps: technical feature vector mining, text vector clustering, and automated phrase mining.

1. Technical feature vector mining based on the ALBERT algorithm: ALBERT builds upon BERT, with improvements aimed at enhancing the model efficiency and scalability. ALBERT achieves this by optimizing the parameter sharing in BERT, reducing the model's spatial complexity from 108 million to 12 million parameters. This results in an improved training efficiency and improved generalization capabilities. In this paper, ALBERT was employed for mining technical features, aiming to achieve a unified representation of multi-source text data in the same semantic vector space.
2. Clustering feature vectors using the K-medoids algorithm: K-medoids is a clustering algorithm based on actual data points, representing an enhancement over the K-means algorithm. It employs actual data points as cluster centroids instead of the mean points, enhancing the robustness and making it capable of handling noisy data and outliers. K-medoids can better adapt to various data distributions.

3. YAKE algorithm (Yet Another Keyword Extractor): YAKE is an unsupervised, machine learning, and statistical-method-based algorithm for extracting key phrases. It starts by preprocessing the text, including operations like part-of-speech tagging and stemming. Next, it calculates importance scores for each word using a series of statistical features such as the TF-IDF, text frequency, text length, etc. Finally, unsupervised machine learning techniques are used to rank these scores, with higher-ranking phrases being considered more important. Unlike other phrase-mining algorithms, YAKE does not require specific prior knowledge and can be applied to various types of texts. Moreover, the extracted key phrases exhibit diversity, covering different themes and contexts within the text.

2.2.3. Identifying Evolutionary Trajectories Through a Temporal Theme Association Analysis

Analyzing annual data for each dimension can reveal more information. Therefore, before conducting a temporal theme analysis, it was necessary to perform time slicing on both the paper and patent data. This involved dividing the data into several intervals and assigning texts to the corresponding time intervals based on their publication years.

The process of time slicing for both the paper and patent data is detailed in Table 1, resulting in a division into six distinct time intervals. Subsequently, an analysis of temporal theme evolution was carried out utilizing these six intervals.

Table 1. Time interval division.

Time Slice Serial Number	1	2	3	4	5	6
Time segment	2003–2006	2007–2010	2011–2013	2014–2016	2017–2019	2020–2022

After temporal segmentation, we obtained the discrete distributions of themes and their associated phrases across various time intervals. To evaluate the relationships between these discretely distributed themes, the average cosine similarity method was applied. The similarity between the average theme vectors was interpreted as the semantic similarity of the themes, as these vectors were derived from the semantic space. The specific process is outlined as follows:

1. Separation of document clusters and feature extraction: First, each theme's corresponding set of phrases (document clusters) is separated by time intervals. The document indices are then used to retrieve the corresponding text representation vectors (document vectors), which are obtained from the previous topic extraction process.

2. Calculation of theme average vectors: After retrieving the document vectors, the next step is to compute their average to generate a representative vector for each theme, referred to as the theme vector. Assuming a theme contains multiple documents, each represented by a high-dimensional feature vector, the average of these vectors provides the semantic representation of the theme, termed the average theme vector. This vector serves as a comprehensive representation of the theme within the semantic space.

3. Cosine similarity calculation: For distinct themes across adjacent time intervals (referred to as theme pairs), cosine similarity is employed to measure their semantic similarity. The cosine similarity (*sim*) is defined as follows.

$$\text{sim}(A, B) = 1 - \frac{\sum_{i=1}^n A_i \cdot B_i}{\sqrt{\sum_{i=1}^n A_i^2} \cdot \sqrt{\sum_{i=1}^n B_i^2}} \quad (1)$$

where A_i and B_i are vectors from the matrix. This calculation produces a value between 0 and 1, where a value closer to 0 indicates greater semantic similarity between the themes [69].

4. Setting the similarity threshold: The association between different themes depends on the selection of the similarity threshold, with the aim of maximizing meaningful information while minimizing noise. A traditional approach was adopted in this study to set the threshold, reducing invalid associations and minimizing noise. Specifically, themes with fewer documents were excluded, and the first significant inflection point on the cosine similarity curve was selected as the threshold. This ensured the reliability and interpretability of the associations, leading to a more structured, comprehensible, and informative technology roadmap.

2.2.4. Inter-Layer Associations and Visualization of the Technology Roadmap

This paper primarily extends upon the TextFlow-based ThemeRiver map framework discussed in Section 2.1.4, employing D3.js for its implementation. It introduces a visualization solution tailored for multi-dimensional data, specifically designed to represent the evolution paths of themes. This constitutes the significant contribution of this work.

As depicted in Figure 2, which shows the enhanced single-layer ThemeRiver map framework based on the D3.js visualization library, a graphical representation of thematic evolution over time was observed. The red dots situated on the thematic “rivers” signify pivotal themes at each time layer, and the accompanying text labels the themes accordingly. The distinct colors of the river streams symbolize different themes, and the varying thickness of these streams reflects the intensity of key themes throughout the given time periods. Vertical lines intersect the flow at designated intervals, marking the division of time-sliced data.

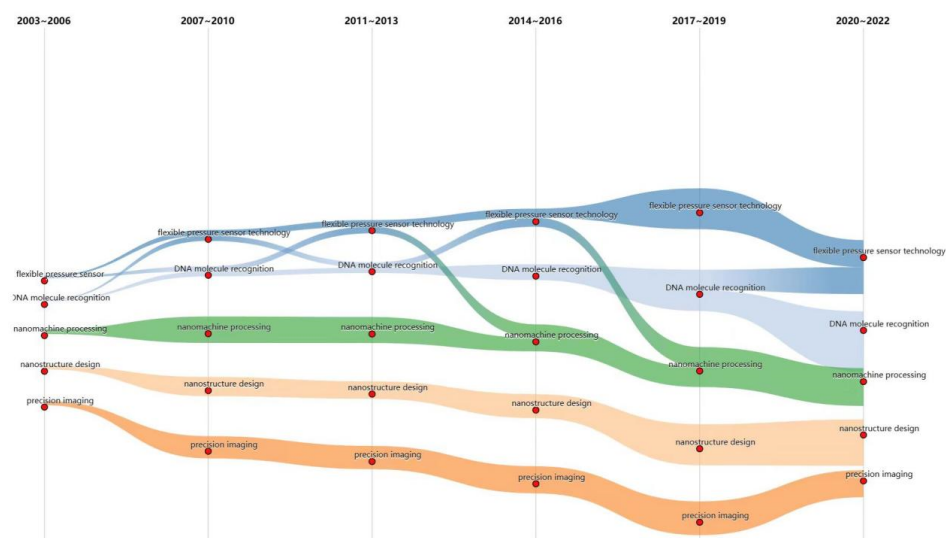


Figure 2. Enhanced Single-Layer Technology ThemeRiver map.

This visualization effectively communicates the dynamic progression and transformation of themes, providing a clear visual narrative of how certain topics have either emerged, developed, or waned in significance over the years. By interacting with the red dots, one can access further details regarding the themes, such as related phrases and connections between them. This facilitates a comprehensive understanding of the thematic landscape within the field under study, demonstrating not only the individual trajectory of each theme, but also their interrelation and overall trends over time.

3. Results and Discussion

3.1. Multi-Source Theme Identification and Association

This section builds on the AKY theme modeling method introduced in Section 2.2, applying it to a tripartite framework comprising the technology, industry, and product layers. The initial phase involves extracting feature vectors from the data within each

layer, utilizing an optimized ALBERT model for this purpose. Following feature extraction, the K-medoids algorithm is applied to conduct a cluster analysis on the feature vectors specific to the technological domain. The optimal number of clusters, referred to as K, is determined using the CH (Calinski–Harabasz) index. For the purpose of this analysis, the technology layer is segmented into five themes, whereas the application layer is dissected into four. Thus, there are nine themes in total for both the technology and application layers, as shown in Table 2.

Table 2. Clustered themes and corresponding top 5 phrases.

Number	Theme	Phrases
1	Flexible pressure sensor technology	Flexible tactile sensor; CNT-based nanodevice; flexible strain; mechanical properties; nano-CW NR matrix
2	DNA molecule recognition	Molecular machine; DNA polymers; DNA computing device; DNA nanotechnology development; DNA surface
3	Precision imaging	Scanning electron microscopy; transmission microscopy; scanning electron; universal testing machine; electron system
4	Nanostructure design	Nanostructure; nanotechnology; performance DT RF model; nanoscale engineering; nanomaterial assembly
5	Nanomachine processing	Nano-surface treatment; nanoprocessing technology; molecular self-assembly; nano-sensors; nanodevices
6	Pollution control	Pollution monitoring; risk assessment; bioaccumulation of nanomaterials; ecological impact; nanoparticle regulation
7	Drug release	Gradual release; drug release pattern; nanomaterial release properties; microenvironment responsiveness; enhanced permeability and retention (EPR) effect
8	Composite preparation	Dispersion performance; synthesis process; nano-coating materials; interface shear; interface modification
9	Treatment monitoring	Nanodrug monitoring; nanoparticle tracking; dynamic observation; nanodrug distribution investigation; real-time monitoring

Once the clustering is complete, theme labels are assigned to each data point, reflecting their membership within the identified clusters. With the YAKE algorithm's parameters duly configured, the subsequent step involves mining for key phrases within each cluster. YAKE is a keyword extraction method based on statistical features that can automatically extract key phrases from text without relying on external corpora, reflecting the core content of each cluster. From this extraction process, the five most representative theme phrases per cluster are identified, as shown in Table 2. These phrases are then synthesized to extract the core themes characteristic of each layer, providing a thematic map that guides the understanding of the data dimensions. These core themes effectively capture the essential content of each cluster, and an in-depth analysis of these themes enables a comprehensive understanding of the potential applications of nanorobotics across various domains. For instance, themes such as “flexible pressure sensor technology” and “nanomachine processing” reflect the application prospects of nanorobotics in manufacturing and biomedicine. Similarly, themes like “DNA molecular recognition” and “precision imaging” highlight the interdisciplinary integration of nanorobotics with fields such as biology and chemistry.

Moreover, themes such as “pollution control” and “drug release” underscore the potential of nanorobotics in environmental protection and precision medicine.

Subsequently, this section methodically sets forth the establishment of theme associations within discrete layers. Initially, technical feature vectors, which are aligned with specific themes, are derived for each time interval. The next step involves computing the average cosine similarity across all the technical feature vectors for each theme within the given time intervals. Thereafter, a critical part of the analysis is defining a similarity threshold, which is pivotal for associating themes, both within the same interval and across various intervals. The task of selecting an appropriate cosine similarity threshold is of paramount importance in theme association. This research aimed to calibrate the threshold at the maximum feasible level that still permits a valid association analysis. This careful calibration is intended to minimize the introduction of extraneous variables and to accentuate the authentic developmental patterns that emerge from the theme evolution analysis.

Upon the computation of cosine similarity for themes across consecutive time intervals, a collection of 405 cosine similarity measures were generated. These measures were arrayed in descending order, from which the uppermost 60 values were chosen for establishing associations, based on the presupposition that themes within identical time intervals are inherently associated. The experimental results yielded a collection of 60 associations between themes. Within this collection, 45 associations were found to be between identical themes, which suggests a persistent or strengthening presence of these themes over the analyzed time periods. The remaining 15 associations were identified amongst distinct themes, suggesting an evolutionary trajectory or convergence between different thematic areas within the time frame analyzed.

To validate our method qualitatively, “flexible pressure sensor technology” as a topic was searched in the Web of Science core collection, showing 1823 science publications from 2023 to 2024. Similarly, searching for “DNA molecule recognition” yielded 1726 publications. The details of the retrieved result are presented in Table 3, which provides qualitative validation that our method successfully identified potential candidates for future research. For each theme, several related papers are referenced in the table.

Table 3. Number of related-topic papers (corresponding to themes from Table 2) from the years 2023 to 2024.

Number	Theme	Paper Number (2023–2024)
1	Flexible pressure sensor technology	1823 [71,72]
2	DNA molecule recognition	1726 [73,74]
3	Precision imaging	20,953 [75]
4	Nanostructure design	2437 [76,77]
5	Nanomachine processing	2433 [78,79]
6	Pollution control	13,715 [80,81]
7	Drug release	27,363 [82,83]
8	Composite preparation	13,784 [84,85]
9	Treatment monitoring	35,885 [86,87]

3.2. Visualization and Comprehensive Analysis of Inter-Layer Association in Multidimensional Technology Roadmapping

This section delves into a detailed visualization and comprehensive analysis of the inter-layer associations in the multidimensional technology roadmap for nanorobotics, drawing from data synthesized from both research papers and patents. Figure 3 illustrates a multi-layer ThemeRiver map, a graphical tool that concurrently represents themes from the technology and application layers, providing a visualization of their temporal evolution. The phrases above the red dots on each river are identical. For example, along the top blue

river, each red dot represents the phrase “flexible pressure technology” across different time segments.

To improve the readability of Figure 3 and provide a clearer understanding of its complex informational structure, Figures 4 and 5 present magnified views of Zones 1 and 2, respectively, from Figure 3.

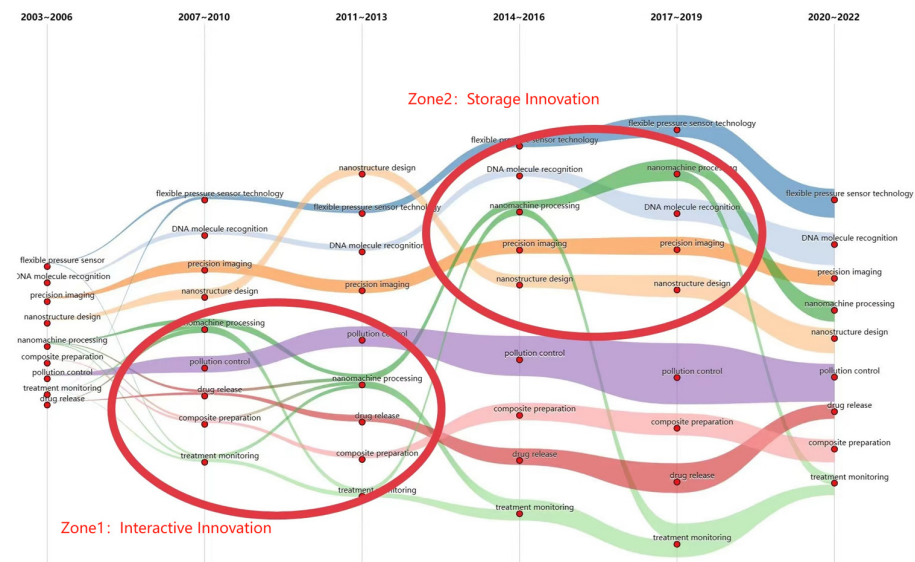


Figure 3. Multi-layer ThemeRiver Map for Nanorobotics.

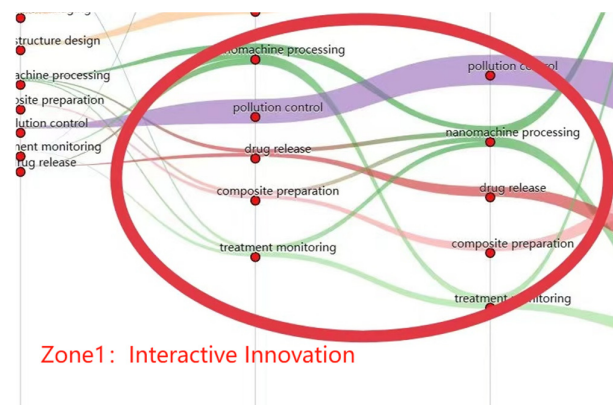


Figure 4. Zoomed-in Zone 1: Interactive Innovation.

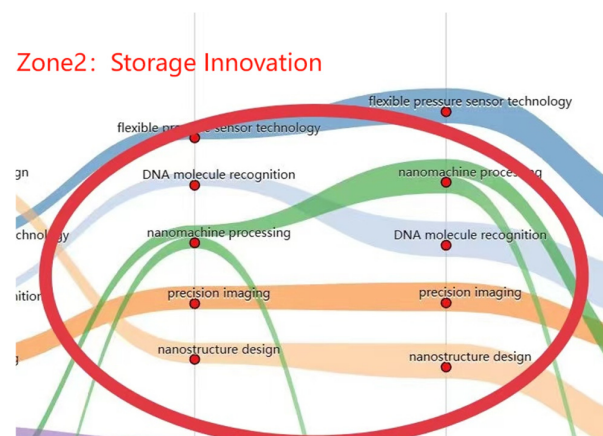


Figure 5. Zoomed-in Zone 2: Storage Innovation.

The map from Figure 3 delineates the development and interconnection of 54 themes over time. The width of the “river” or “flow” correlates with the relative prominence of each theme during different time frames, indicating their respective impacts within the industrial robotics sector. The upper five streams of the river map trace the thematic changes within the technology layer, while the lower four streams pertain to the application layer.

An examination of the overall river map revealed that, prior to 2014, the theme intensities were comparatively subdued, with the research primarily converging towards precision imaging and pollution control. This suggests that, during this phase, nanorobotics research was in a nascent stage, with significant breakthroughs largely confined to precision imaging and, to a lesser extent, pollution control applications. Post-2014, the themes represented in the subsequent intervals demonstrate a more robust presence, signifying a blossoming of both the development and the industrial application of nanorobot technology. The involvement of researchers from a wide array of disciplines signaled a flourishing period of research and development activity.

In Zone 1, spanning 2007–2010 and 2011–2013, despite the modest strengths of themes, there was a notable incidence of associations, mergers, and divergences between themes across the two dimensions of nanorobotics. For instance, flexible pressure sensor technology was seen converging with nanomachine processing in the context of treatment monitoring applications. Additionally, nanomachine processing experienced a confluence and subsequent separation with treatment monitoring and drug release applications. This trend underscores a period of dynamic interaction and the integration of technology and applications, and is thus termed “interactive innovation”.

This dynamic interaction observed in our roadmap is less apparent in traditional methods, such as those used by Wang et al. [47] and Liu et al. [49], which tend to present more static representations of technological themes and their applications. By employing multi-dimensional ThemeRiver mapping and cosine similarity, our approach offers a more nuanced view of the interrelationships between technological and application themes, capturing the convergence of themes like “Flexible Pressure Sensor Technology” and “Nanomachine Processing” in a way that earlier methods did not.

Moving to Zone 2, which covers the periods 2014–2016 and 2017–2019, we observe themes with relatively more significant strengths. Nonetheless, the inter-theme activities such as associations, mergers, and splits appear less frequent. Nanomachine processing is observed to interlink and then disassociate with treatment monitoring applications, while other technological and application themes display minimal interconnections. This pattern suggests a period of intensive research focus within nanorobotics, a time when energies were being channeled into the research domain, setting the stage for future bursts of innovative activity, hence termed “Storage Innovation”.

One of the critical observations made in this study is the differentiation of the proposed method from existing approaches, particularly with respect to its capability to capture the complex evolutionary pathways of nanorobotic technologies. In contrast to traditional methods that often rely on a more linear or static representation of technological development, such as those utilized by Wang et al. and Liu et al., our approach utilizes a dynamic and multi-source data framework to map out the interdependencies between various technological themes and their corresponding applications over time [47,49]. While both Wang et al. and Liu et al. demonstrated the effectiveness of combining a bibliometric analysis with patent citation data for roadmap development, these methods are constrained by their reliance on specific datasets and the relatively siloed analysis of technology and application themes. In comparison, our method introduces multi-dimensional ThemeRiver mapping and cosine similarity measures that allow for a more integrated analysis of technological and application layers, providing a more nuanced understanding of the temporal evolution and interaction of different themes. For instance, the clustering of themes like “flexible pressure sensor technology” and “nanomachine processing” in Zone 1 of our roadmap demonstrates a significant improvement in tracking the convergence of technologies and their applications. This level of granularity is less apparent in earlier methods,

where the focus was on overarching trends rather than the detailed interactions between specific themes.

The empirical results presented in this study further highlight the practical advantages of our method. The identified “interactive innovation” phase (2007–2013) and “storage innovation” phase (2014–2019) offer deeper insights into the dynamic interactions between technology and application themes. These findings contrast with the more static representations in traditional roadmaps, where theme interactions are not as explicitly detailed or temporally mapped.

These analyses provide a nuanced view of the multidimensional thematic evolution and associations within the nanorobotics field. They offer invaluable insights for specialists in the domain and for those constructing technology roadmaps. The multi-layer river map not only furnishes a vivid interactive depiction of thematic evolution, but it also augments the efficiency with which experts can interact with data. This sophisticated visual representation and the accompanying comprehensive analysis serve as pivotal elements in the development of a technology roadmap, ensuring the communication of high-quality information for strategic planning and forecasting in the realm of nanorobotics.

4. Conclusions

This paper addresses the prevalent challenges of an insufficient analytical depth and a singular analytical perspective within the study of nanorobotics technology roadmaps. A novel theme modeling method, termed AKY, for multi-source text mining was introduced, along with a multi-layer river map approach to visualize inter-layer associations in technology roadmaps, thus enabling a multidimensional analysis of thematic evolution by effectively integrating multiple data sources with expert knowledge. Consequently, it facilitates the rapid identification of key themes by experts, thereby improving both the quality and efficiency of the nanorobotics technology roadmap development process.

The implementation of automated phrase-mining algorithms has been demonstrated to enrich the thematic content and augment its interpretability. For instance, in the nanorobotics technology roadmap outlined in this document, key themes such as treatment monitoring and flexible pressure sensor technology were significantly expanded. Moreover, the utilization of technology feature vector mining, which unifies disparate data sources and types into a singular vector space, combined with clustering algorithms, effectively facilitated the correlation of multi-source text data. An analysis of the inter-layer associations on the river map revealed that the current focal points of nanorobotics technology development are centered around DNA molecule recognition and flexible pressure sensor technology, with significant potential applications in pollution control and treatment monitoring.

However, several limitations of the current research need to be acknowledged, along with recommendations for future research:

1. **Focus on technological development:** The technology roadmap encompasses two key dimensions: the intrinsic development of technology, which follows its natural trajectory, and the market-driven forces that influence how technology impacts the market. Our study primarily focused on the intrinsic technological progression without addressing the impact of market forces. While the analysis effectively captured the natural development trends in nanorobotics, future research should incorporate market dynamics to provide a more comprehensive roadmap. For instance, integrating expert knowledge could further enhance the analysis and help develop a roadmap that accounts for both technological advancements and their market implications.

2. **Scalability and Adaptability to Other Domains:** While the AKY method and multi-layer ThemeRiver model have proven effective for analyzing nanorobotics, their scalability and adaptability to other technological domains or industrial sectors remain to be tested. Future research could focus on applying this framework to other emerging technologies, such as artificial intelligence, renewable energy, or biotechnology, to evaluate its flexibility and usefulness across a range of fields. Comparative studies between these dif-

ferent applications would provide valuable insights into the framework's generalizability and scalability.

In conclusion, this research introduced a pioneering approach to deepen and broaden the analysis of nanorobotics technology roadmaps. It provides significant insights into the development trends and key themes within the field, while laying the groundwork for future improvements, particularly in the areas of data integration, empirical validation, and applications across broader technological landscapes.

Author Contributions: Conceptualization, H.L. and Y.L.; methodology, R.Z.; software, R.Z. and Y.H.; validation, H.L., Y.L. and Z.L.; formal analysis, R.Z. and Y.H.; investigation, Z.L.; resources, Z.L.; writing—original draft preparation, R.Z. and Z.L.; writing—review and editing, Z.L. and Y.H.; visualization, R.Z. and Z.L.; supervision, H.L. and Y.L.; funding acquisition, H.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China [grant number 72104224]; the Construction Project of China Knowledge Center for Engineering Sciences and Technology [grant number CKCEST-2023-1-7]; and the Ministry of Science and Technology of the People's Republic of China [grant number 2018YFB1701003].

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Acknowledgments: Artificial intelligence was used to proofread the content of this paper.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Zhou, Y.; Dong, F.; Kong, D.; Liu, Y. Unfolding the Convergence Process of Scientific Knowledge for the Early Identification of Emerging Technologies. *Technol. Forecast. Soc. Chang.* **2019**, *144*, 205–220. [\[CrossRef\]](#)
2. Zhang, J.; Hu, K.; Di, L.; Wang, P.; Liu, Z.; Zhang, J.; Yue, P.; Song, W.; Zhang, J.; Chen, T.; et al. Traditional Herbal Medicine and Nanomedicine: Converging Disciplines to Improve Therapeutic Efficacy and Human Health. *Adv. Drug Deliv. Rev.* **2021**, *178*, 113964. [\[CrossRef\]](#) [\[PubMed\]](#)
3. Yamashita, Y.; Tsurumi, J.; Ohno, M.; Fujimoto, R.; Kumagai, S.; Kurosawa, T.; Okamoto, T.; Takeya, J.; Watanabe, S. Efficient Molecular Doping of Polymeric Semiconductors Driven by Anion Exchange. *Nature* **2019**, *572*, 634–638. [\[CrossRef\]](#)
4. Hu, X.; Hu, R.; Wu, X.; Songsun, F.; Zhu, H.; Chen, J.; Chen, H. Self-Assembled Fabrication of Water-Soluble Porphyrin Mediated Supramolecule-Gold Nanoparticle Networks and Their Application in Selective Sensing. *Bull. Chem. Soc. Jpn.* **2021**, *94*, 2662–2669. [\[CrossRef\]](#)
5. Okamoto, T.; Yu, C.P.; Mitsui, C.; Yamagishi, M.; Ishii, H.; Takeya, J. Bent-Shaped p-Type Small Molecule Organic Semiconductors: A Molecular Design Strategy for Next-Generation Practical Applications. Semantic Scholar. Available online: <https://www.semanticscholar.org/paper/Bent-Shaped-p-Type-Small-Molecule-Organic-A-Design-Okamoto-Yu/abc0fa8970170d944ab489b598eb0465e3e7943a> (accessed on 28 April 2024).
6. Chaovalitwongse, W.A.; Yuan, Y.; Zhang, Q.; Liu, J. Special Issue: Innovative Applications of Big Data and Artificial Intelligence. *Front. Eng. Manag.* **2022**, *9*, 517–519. [\[CrossRef\]](#)
7. Zhou, Y.; Dong, F.; Liu, Y.; Ran, L. A Deep Learning Framework to Early Identify Emerging Technologies in Large-Scale Outlier Patents: An Empirical Study of CNC Machine Tool. *Scientometrics* **2021**, *126*, 969–994. [\[CrossRef\]](#)
8. Zhou, Y.; Miao, Z.; Urban, F. China's Leadership in the Hydropower Sector: Identifying Green Windows of Opportunity for Technological Catch-Up. *Ind. Corp. Chang.* **2021**, *29*, 1319–1343. [\[CrossRef\]](#)
9. Zhou, Y.; Li, X.; Lema, R.; Urban, F. Comparing the Knowledge Bases of Wind Turbine Firms in Asia and Europe: Patent Trajectories, Networks, and Globalisation. *Sci. Public Policy* **2016**, *43*, 476–491. [\[CrossRef\]](#)
10. Lenaghan, S.C.; Wang, Y.; Xi, N.; Fukuda, T.; Tarn, T.; Hamel, W.R.; Zhang, M. Grand Challenges in Bioengineered Nanorobotics for Cancer Therapy. *IEEE Trans. Biomed. Eng.* **2013**, *60*, 667–673. [\[CrossRef\]](#)
11. Zhou, Y.; Dong, F.; Liu, Y.; Li, Z.; Du, J.; Zhang, L. Forecasting Emerging Technologies Using Data Augmentation and Deep Learning. *Scientometrics* **2020**, *123*, 1–29. [\[CrossRef\]](#)
12. Cavalcanti, A.; Shirinzadeh, B.; Freitas, R.A.; Hogg, T. Nanorobot Architecture for Medical Target Identification. *Nanotechnology* **2007**, *19*, 015103. [\[CrossRef\]](#)

13. Phaal, R.; Farrukh, C.J.P.; Probert, D.R. Characterisation of Technology Roadmaps: Purpose and Format. In Proceedings of the PICMET '01. Portland International Conference on Management of Engineering and Technology, Portland, OR, USA, 29 July–2 August 2001; Volume 1, p. 192.
14. Lan, Z.; Chen, M.; Goodman, S.; Gimpel, K.; Sharma, P.; Soricut, R. Albert: A Lite Bert for Self-Supervised Learning of Language Representations. *arXiv* **2020**, arXiv:1909.11942.
15. Liu, Y.; Ott, M.; Goyal, N.; Du, J.; Joshi, M.; Chen, D.; Levy, O.; Lewis, M.; Zettlemoyer, L.; Stoyanov, V. RoBERTa: A Robustly Optimized BERT Pretraining Approach. *arXiv* **2019**, arXiv:1907.11692.
16. Xu, G.; Zhou, Y.; Ji, H. How Can Government Promote Technology Diffusion in Manufacturing Paradigm Shift? Evidence From China. *IEEE Trans. Eng. Manag.* **2023**, *70*, 1547–1559. [[CrossRef](#)]
17. Feynman, R.P. There's Plenty of Room at the Bottom. *Eng. Sci.* **1959**, *23*, 63–76.
18. Qiu, F.; Nelson, B.J. Magnetic Helical Micro- and Nanorobots: Toward Their Biomedical Applications. *Engineering* **2015**, *1*, 021–026. [[CrossRef](#)]
19. Sugimoto, Y.; Pou, P.; Abe, M.; Jelinek, P.; Pérez, R.; Morita, S.; Custance, Ó. Chemical Identification of Individual Surface Atoms by Atomic Force Microscopy. *Nature* **2007**, *446*, 64–67. [[CrossRef](#)]
20. Bacilla, A.C.C.; Okada, Y.; Yoshimoto, S.; Islyaikin, M.K.; Koifman, O.I.; Kobayashi, N. Triangular Expanded Hemiporphyrazines: Electronic Structures and Nanoscale Characterization of Their Adlayers on Au(111). *Bull. Chem. Soc. Jpn.* **2021**, *94*, 34–43. [[CrossRef](#)]
21. Kratish, Y.; Nakamuro, T.; Liu, Y.; Li, J.; Tomotsuka, I.; Harano, K.; Nakamura, E.; Marks, T.J. Synthesis and Characterization of a Well-Defined Carbon Nanohorn-Supported Molybdenum Dioxo Catalyst by SMART-EM Imaging. Surface Structure at the Atomic Level. *Bull. Chem. Soc. Jpn.* **2021**, *94*, 427–432. [[CrossRef](#)]
22. Kimura, K.; Miwa, K.; Imada, H.; Imai-Imada, M.; Kawahara, S.; Takeya, J.; Kawai, M.; Galperin, M.; Kim, Y. Selective Triplet Exciton Formation in a Single Molecule. *Nature* **2019**, *570*, 210–213. [[CrossRef](#)]
23. Miyamoto, M.; Hada, M. IR Intensities of CO Molecules Adsorbed on Atop and Low-Coordinate Sites of Pd Nanoparticles: Analysis Using Natural Perturbation Orbitals. *Bull. Chem. Soc. Jpn.* **2021**, *94*, 1789–1793. [[CrossRef](#)]
24. Imada, H.; Imai-Imada, M.; Miwa, K.; Yamane, H.; Iwasa, T.; Tanaka, Y.; Toriumi, N.; Kimura, K.; Yokoshi, N.; Muranaka, A.; et al. Single-Molecule Laser Nanospectroscopy with Micro-Electron Volt Energy Resolution. *Science* **2021**, *373*, 95–98. [[CrossRef](#)] [[PubMed](#)]
25. Sugimoto, Y.; Pou, P.; Custance, O.; Jelinek, P.; Abe, M.; Perez, R.; Morita, S. Complex Patterning by Vertical Interchange Atom Manipulation Using Atomic Force Microscopy. *Science* **2008**, *322*, 413–417. [[CrossRef](#)] [[PubMed](#)]
26. Ishida, Y. Manipulation of Precise Molecular Arrangements and Their Photochemical Properties on Inorganic Surfaces via Multiple Electrostatic Interactions. *Bull. Chem. Soc. Jpn.* **2021**, *94*, 2886–2897. [[CrossRef](#)]
27. Ishihara, H. Optical Manipulation of Nanoscale Materials by Linear and Nonlinear Resonant Optical Responses. *Adv. Phys. X* **2021**, *6*, 1885991. [[CrossRef](#)]
28. Zhang, Z.; Chen, Y.; Klausen, L.H.; Skaavik, S.A.; Wang, D.; Chen, J.; Dong, M. The Rational Design and Development of Microalgae-Based Biohybrid Materials for Biomedical Applications. *Engineering* **2023**, *24*, 102–113. [[CrossRef](#)]
29. Miao, J.; Zhang, T.; Li, G.; Guo, D.; Sun, S.; Tan, R.; Shi, J.; Shen, Y. Flagellar/Ciliary Intrinsic Driven Mechanism Inspired All-in-One Tubular Robotic Actuator. *Engineering* **2023**, *23*, 170–180. [[CrossRef](#)]
30. Lin, H.; Zeng, S.; Liu, H.; Li, C. Bridging the Gaps or Fecklessness? A Moderated Mediating Examination of Intermediaries' Effects on Corporate Innovation. *Technovation* **2020**, *94*, 102018. [[CrossRef](#)]
31. Xu, L.; Gong, D.; Chen, K.; Cai, J.; Zhang, W. Acoustic Levitation Applied for Reducing Undesired Lateral Drift of Magnetic Helical Microrobots. *J. Appl. Phys.* **2020**, *128*, 184703. [[CrossRef](#)]
32. Qin, N.; Qian, Z.-G.; Zhou, C.; Xia, X.-X.; Tao, T.H. 3D Electron-Beam Writing at Sub-15 Nm Resolution Using Spider Silk as a Resist. *Nat. Commun.* **2021**, *12*, 5133. [[CrossRef](#)]
33. Terzopoulou, A.; Wang, X.; Chen, X.; Palacios-Corella, M.; Pujante, C.; Herrero-Martín, J.; Qin, X.; Sort, J.; deMello, A.J.; Nelson, B.J.; et al. Biodegradable Metal–Organic Framework-Based Microrobots (MOFBOTs). *Adv. Healthc. Mater.* **2020**, *9*, 2001031. [[CrossRef](#)] [[PubMed](#)]
34. Kishore, C.; Bhadra, P. Targeting Brain Cancer Cells by Nanorobot, a Promising Nanovehicle: New Challenges and Future Perspectives. *CNS Neurol. Disord. Drug Targets* **2021**, *20*, 531–539. [[CrossRef](#)] [[PubMed](#)]
35. Lin, Z.; Gao, C.; Wang, D.; He, Q. Bubble-Propelled Janus Gallium/Zinc Micromotors for the Active Treatment of Bacterial Infections. *Angew. Chem. Int. Ed. Engl.* **2021**, *60*, 8750–8754. [[CrossRef](#)] [[PubMed](#)]
36. Wang, J.; Toebes, B.J.; Plachokova, A.S.; Liu, Q.; Deng, D.; Jansen, J.A.; Yang, F.; Wilson, D.A. Self-Propelled PLGA Micromotor with Chemotactic Response to Inflammation. *Adv. Healthc. Mater.* **2020**, *9*, e1901710. [[CrossRef](#)]
37. Schwarz, L.; Karnaushenko, D.D.; Hebenstreit, F.; Naumann, R.; Schmidt, O.G.; Medina-Sánchez, M. A Rotating Spiral Micromotor for Noninvasive Zygote Transfer. *Adv. Sci.* **2020**, *7*, 2000843. [[CrossRef](#)]
38. Ahmed, S.; Wang, W.; Bai, L.; Gentekos, D.T.; Hoyos, M.; Mallouk, T.E. Density and Shape Effects in the Acoustic Propulsion of Bimetallic Nanorod Motors. *ACS Nano* **2016**, *10*, 4763–4769. [[CrossRef](#)]
39. Magdanz, V.; Khalil, I.S.M.; Simmchen, J.; Furtado, G.P.; Mohanty, S.; Gebauer, J.; Xu, H.; Klingner, A.; Aziz, A.; Medina-Sánchez, M.; et al. IRONSperm: Sperm-Templated Soft Magnetic Microrobots. *Sci. Adv.* **2020**, *6*, eaba5855. [[CrossRef](#)]

40. Jeong, Y.; Yoon, B. Development of Patent Roadmap Based on Technology Roadmap by Analyzing Patterns of Patent Development. *Technovation* **2015**, *39*, 37–52. [CrossRef]
41. Zhou, Y.; Phaal, R.; Farrukh, C.; Probert, D. Innovation and Strategy Roadmap: Theory, Methods, and Applications. Available online: <https://book.sciencereading.cn/shop/book/Booksimple/show.do?id=BBFD70F1D4764BAB6E053020B0A0A1375000> (accessed on 11 March 2024).
42. Phaal, R.; Farrukh, C.J.P.; Probert, D.R. Technology Roadmapping—A Planning Framework for Evolution and Revolution. *Technol. Forecast. Soc. Chang.* **2004**, *71*, 5–26. [CrossRef]
43. An, Y.; Lee, S.; Park, Y. Development of an Integrated Product-service Roadmap with QFD: A Case Study on Mobile Communications. *Int. J. Serv. Ind. Manag.* **2008**, *19*, 621–638. [CrossRef]
44. Lee, J.H.; Phaal, R.; Lee, C. An Empirical Analysis of the Determinants of Technology Roadmap Utilization. *RD Manag.* **2011**, *41*, 485–508. [CrossRef]
45. Yuan, B.J.C.; Yi Liu, C.; Chuan Ho, S.; Kao, H.K.M.; Chang Shen, P. An Application of a Foresight-based New Product Planning Model: A Case Study of a Large Household Appliance Manufacturer in China. *Chin. Manag. Stud.* **2012**, *6*, 444–461. [CrossRef]
46. Lee, S.; Yoon, B.; Lee, C.; Park, J. Business Planning Based on Technological Capabilities: Patent Analysis for Technology-Driven Roadmapping. *Technol. Forecast. Soc. Chang.* **2009**, *76*, 769–786. [CrossRef]
47. Wang, B.; Liu, Y.; Zhou, Y.; Wen, Z. Emerging Nanogenerator Technology in China: A Review and Forecast Using Integrating Bibliometrics, Patent Analysis and Technology Roadmapping Methods. *Nano Energy* **2018**, *46*, 322–330. [CrossRef]
48. Chen, X.; Tang, X.; Xu, X. Digital Technology-Driven Smart Society Governance Mechanism and Practice Exploration. *Front. Eng. Manag.* **2023**, *10*, 319–338. [CrossRef]
49. Liu, H.; Zhang, R.; Liu, Y.; He, C. Unveiling Evolutionary Path of Nanogenerator Technology: A Novel Method Based on Sentence-BERT. *Nanomaterials* **2022**, *12*, 2018. [CrossRef]
50. Liu, Y.; Wang, G.; Zhou, Y.; Liu, Y. Advanced Technology Evolution Pathways of Nanogenerators: A Novel Framework Based on Multi-Source Data and Knowledge Graph. *Nanomaterials* **2022**, *12*, 838. [CrossRef]
51. Kerr, C.; Phaal, R.; Thams, K. Customising and Deploying Roadmapping in an Organisational Setting: The LEGO Group Experience. *J. Eng. Technol. Manag.* **2019**, *52*, 48–60. [CrossRef]
52. Geum, Y.; Lee, H.; Lee, Y.; Park, Y. Development of Data-Driven Technology Roadmap Considering Dependency: An ARM-Based Technology Roadmapping. *Technol. Forecast. Soc. Chang.* **2015**, *91*, 264–279. [CrossRef]
53. Zhou, Y.; Liu, Y.; Xue, L. An Approach to Identify Emerging Technologies Using Machine Learning: A Case Study of Robotics. *J. China Soc. Sci. Tech. Inf.* **2018**, *37*, 939–955. [CrossRef]
54. Kim, J.; Park, Y.; Lee, Y. A Visual Scanning of Potential Disruptive Signals for Technology Roadmapping: Investigating Keyword Cluster, Intensity, and Relationship in Futuristic Data. *Technol. Anal. Strateg. Manag.* **2016**, *28*, 1225–1246. [CrossRef]
55. Lahoti, G.; Porter, A.L.; Zhang, C.; Youtie, J.; Wang, B. Tech Mining to Validate and Refine a Technology Roadmap. *World Pat. Inf.* **2018**, *55*, 1–18. [CrossRef]
56. Shibata, N.; Kajikawa, Y.; Sakata, I. Extracting the Commercialization Gap between Science and Technology—Case Study of a Solar Cell. *Technol. Forecast. Soc. Chang.* **2010**, *77*, 1147–1155. [CrossRef]
57. Mejia, C.; Kajikawa, Y. Emerging Topics in Energy Storage Based on a Large-Scale Analysis of Academic Articles and Patents. *Appl. Energy* **2020**, *263*, 114625. [CrossRef]
58. Kong, D.; Zhou, Y.; Liu, Y.; Xue, L. Using the Data Mining Method to Assess the Innovation Gap: A Case of Industrial Robotics in a Catching-up Country. *Technol. Forecast. Soc. Chang.* **2017**, *119*, 80–97. [CrossRef]
59. Havre, S.; Hetzler, E.; Whitney, P.; Nowell, L. ThemeRiver: Visualizing Thematic Changes in Large Document Collections. *IEEE Trans. Visual. Comput. Graph.* **2002**, *8*, 9–20. [CrossRef]
60. Mazza, R. Introduction to Information Visualization. SpringerLink. Available online: <https://link.springer.com/book/10.1007/978-1-84800-219-7> (accessed on 11 March 2024).
61. Cui, W.; Liu, S.; Tan, L.; Shi, C.; Song, Y.; Gao, Z.; Qu, H.; Tong, X. TextFlow: Towards Better Understanding of Evolving Topics in Text. *IEEE Trans. Visual. Comput. Graph.* **2011**, *17*, 2412–2421. [CrossRef]
62. Malik, S.; Smith, A.; Hawes, T.; Papadatos, P.; Li, J.; Dunne, C.; Shneiderman, B. TopicFlow: Visualizing Topic Alignment of Twitter Data over Time. In Proceedings of the 2013 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM 2013), Niagara, ON, Canada, 25–28 August 2013; pp. 720–726.
63. Wu, Y.; Liu, S.; Yan, K.; Liu, M.; Wu, F. OpinionFlow: Visual Analysis of Opinion Diffusion on Social Media. *IEEE Trans. Visual. Comput. Graph.* **2014**, *20*, 1763–1772. [CrossRef]
64. Wongsuphasawat, K.; Guerra Gómez, J.A.; Plaisant, C.; Wang, T.D.; Taieb-Maimon, M.; Shneiderman, B. LifeFlow: Visualizing an Overview of Event Sequences. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Vancouver, BC, Canada, 7–12 May 2011; pp. 1747–1756. [CrossRef]
65. Dou, W.; Yu, L.; Wang, X.; Ma, Z.; Ribarsky, W. HierarchicalTopics: Visually Exploring Large Text Collections Using Topic Hierarchies. *IEEE Trans. Visual. Comput. Graph.* **2013**, *19*, 2002–2011. [CrossRef]
66. Liu, D.; Xu, P.; Ren, L. TPFLOW: Progressive Partition and Multidimensional Pattern Extraction for Large-Scale Spatio-Temporal Data Analysis. *IEEE Trans. Visual. Comput. Graph.* **2019**, *25*, 1–11. [CrossRef]
67. Imrich, P.; Mueller, K.; Imre, D.; Zelenyuk, A.; Zhu, W. Interactive Poster: 3D ThemeRiver. In Proceedings of the IEEE Symposium on Information Visualization, Seattle, WA, USA, 19–24 October 2003.

68. Blei, D.M.; Ng, A.Y.; Jordan, M.I. Latent Dirichlet Allocation. *J. Mach. Learn. Res.* **2003**, *3*, 993–1022.
69. Manning, C.D.; Raghavan, P.; Schütze, H. Introduction to Information Retrieval. Available online: <https://www.cambridge.org/highereducation/books/introduction-to-information-retrieval/669D108D20F556C5C30957D63B5AB65C> (accessed on 11 March 2024).
70. Xiang, Q.; Zhang, Y.; Zhong, J.; Wang, G.; Long, L. Construction of Digital 3D Magic-Cube Organization Structure for Innovation-Driven Manufacturing. *Front. Eng. Manag.* **2023**, *10*, 373–390. [\[CrossRef\]](#)
71. Bi, S.; Jin, W.; Han, X.; Metts, J.; Ostrosky, A.D.; Lehotsky, J.; He, Z.; Jiang, C.; Asare-Yeboah, K. Flexible Pressure Visualization Equipment for Human-Computer Interaction. *Mater. Today Sustain.* **2023**, *21*, 100318. [\[CrossRef\]](#)
72. Han, S.; Li, S.; Fu, X.; Han, S.; Chen, H.; Zhang, L.; Wang, J.; Sun, G. Research Progress of Flexible Piezoresistive Sensors Based on Polymer Porous Materials. *ACS Sens.* **2024**, *9*, 3848–3863. [\[CrossRef\]](#)
73. Wang, Y.; Ren, L.; Peng, H.; Guo, L.; Wang, L. DNA-Programmed Biomolecular Spatial Pattern Recognition. *Chemosensors* **2023**, *11*, 362. [\[CrossRef\]](#)
74. Zhang, C.; Zhao, J.; Lu, B.; Seeman, N.C.; Sha, R.; Noinaj, N.; Mao, C. Engineering DNA Crystals toward Studying DNA–Guest Molecule Interactions. *J. Am. Chem. Soc.* **2023**, *145*, 4853–4859. [\[CrossRef\]](#)
75. Kumar, V.; Singh, A.K.; Damasevicius, R. Guest Editorial Artificial Intelligence-Driven Biomedical Imaging Systems for Precision Diagnostic Applications. *IEEE J. Biomed. Health Inform.* **2024**, *28*, 1158–1160. [\[CrossRef\]](#)
76. Puspaduhita, A.; Surawijaya, A.; Anshori, I. Optical Characteristic Measurement of Micro/Nanodroplet on Embedded Grating Nanostructure for Digital Microfluidic’s Electrode. *IEEE Access* **2023**, *11*, 137115–137124. [\[CrossRef\]](#)
77. Huang, J.; Wang, L.; Wang, B.; Liu, G.; Wang, W.; Ge, C. Research Progress on Modulation of Electromagnetic Performance through Micro-Nanostructure Design. *J. Inorg. Mater.* **2024**, *39*, 853. [\[CrossRef\]](#)
78. Zheng, H.; Li, H.; Li, M.; Zhai, T.; Xie, X.; Li, C.; Jing, X.; Liang, C.; Li, Q.; Zuo, X.; et al. A Membrane Tension-Responsive Mechanosensitive DNA Nanomachine. *Angew. Chem. Int. Ed.* **2023**, *62*, e202305896. [\[CrossRef\]](#)
79. Yang, H.; Kang, S.; Du, Z.; Dong, Y.; Fang, B.; Zhan, J.; Xu, W.; Zhu, L. Magnetic DNAzyme Nanomachine Fluorescent Biosensor for Pb(II) Detection. *Sens. Actuators B Chem.* **2024**, *405*, 135332. [\[CrossRef\]](#)
80. Li, Z.; Zhao, K.; Yuan, X.; Zhou, Y.; Yang, L.; Geng, H. Evolution and Control of Air Pollution in China over the Past 75 Years: An Analytical Framework Based on the Multi-Dimensional Urbanization. *Atmosphere* **2024**, *15*, 1093. [\[CrossRef\]](#)
81. Zhao, Y.; Peng, Z.; Zhou, Z.; Zhai, X.; Gong, S.; Shen, C.; Zhang, T.; Zhao, D.; Cao, D. The Impact of Air Pollution Controls on Health and Health Inequity Among Middle-Aged and Older Chinese: Evidence from Panel Data. *Int. J. Public Health* **2024**, *69*, 1606956. [\[CrossRef\]](#) [\[PubMed\]](#)
82. Zhang, T.; Liu, N.; Xie, C.; Xiao, X. Self-trigger and On-demand Drug Delivery System Based on TiO₂ Nanotube Arrays and Its Drug Release Behaviour. *Micro Nano Lett.* **2023**, *18*, e12173. [\[CrossRef\]](#)
83. Tian, M.; Zhu, Y.; Guan, W.; Lu, C. Quantitative Measurement of Drug Release Dynamics within Targeted Organelles Using Förster Resonance Energy Transfer. *Small* **2023**, *19*, 2206866. [\[CrossRef\]](#)
84. Tarhini, A.; Tehrani-Bagha, A.R. Advances in Preparation Methods and Conductivity Properties of Graphene-Based Polymer Composites. *Appl. Compos. Mater.* **2023**, *30*, 1737–1762. [\[CrossRef\]](#)
85. Li, C.; Li, W.; Wu, G.; Chen, G.; Wu, J.; Zhang, N.; Gan, Y.; Zhang, D.; Chen, C. Design and Study of Composite Film Preparation Platform. *Crystals* **2024**, *14*, 389. [\[CrossRef\]](#)
86. Su, T.; Zhao, F.; Ying, Y.; Li, W.; Li, J.; Zheng, J.; Qiao, L.; Che, S.; Yu, J. Self-Monitoring Theranostic Nanomaterials: Emerging Visual Agents for Real-Time Monitoring of Tumor Treatment Processes. *Small Methods* **2024**, *8*, 2301470. [\[CrossRef\]](#)
87. Kojder, K.; Jarosz, K.; Andrzejewska, A.; Kubiak, K.; Poncyljusz, W.; Solec-Pastuszka, J. Noninvasive Monitoring in a Patient with SAH Diagnosis Treated with Cerebrolysin—Case Report and Review of the Literature. *Eur. Rev. Med. Pharmacol. Sci.* **2023**, *27*, 6843–6849. [\[CrossRef\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.