Technology Foresight: State of the Art, Trends, and Future Reflections from a Data Analytics Perspective - Postprint

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Abstract

[Purpose/Significance] From a data analysis perspective and based on the evolution of research data and methodologies, this study conducts a systematic analysis of technology forecasting research.

[Method/Process] To clarify the developmental trajectory, this study categorizes data analysis-based technology forecasting research into four stages: the embryonic stage (1981-1991), the growth stage (1992-2010), the expansion stage (2011-2017), and the bottleneck stage (2018-present). Through the integrated application of bibliometric methods and knowledge graph analysis tools, an in-depth analysis of the research frontiers at each stage is performed.

[Results/Conclusion] The findings indicate that technology forecasting has consistently evolved toward a multi-level, systematic direction, yet has not accomplished the transition from "how technology might develop" to "how technology should develop" within complex environments. Establishing scientific data sharing platforms, developing intelligent analysis software, and exerting the government's macro-regulatory functions will be focal points for future attention.

Full Text

Technology Forecasting Research: Current Status, Trends, and Future Perspectives from a Data Analytics Perspective

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Abstract: [Purpose/Significance] From a data analytics perspective, this paper systematically analyzes technology forecasting research based on the evolution of research data and methodologies. [Method/Process] To clarify its developmental trajectory, this study divides data-driven technology forecasting research into four stages: the nascent phase (1981–1991), growth phase (1992–2010), expansion phase (2011–2017), and bottleneck phase (2018–present). Through comprehensive application of bibliometric methods and knowledge mapping analysis tools, we conduct in-depth analysis of research fronts across different stages. [Result/Conclusion] The findings indicate that technology forecasting has consistently evolved toward a multi-level, systematic direction, yet has not completed the transition from "how technology may develop" to "how technology should develop" in complex environments. Building scientific data sharing platforms, developing intelligent analysis software, and leveraging government macro-control will be focal points for future attention.

Keywords: technology forecasting; data analytics; bibliometrics; research fronts; ITGInsight

1. Introduction

In today's world, rapid technological development has made technological capability a primary indicator for measuring national comprehensive strength. How to formulate rational and effective science and technology development strategies, and to deploy and develop frontier technologies and strategic industries in advance, has become a paramount issue for governments worldwide [1]. In August 2016, the State Council issued the "13th Five-Year National Science and Technology Innovation Plan" (Guofa [2016] No. 43), which clarified the overall approach and development goals for scientific and technological innovation during the 13th Five-Year period, focusing on national strategic and socio-economic development needs, identifying main directions and breakthrough points, and strengthening the research, development, and application of key core technologies [2]. In March 2021, the "14th Five-Year Plan for National Economic and Social Development and Long-Range Objectives Through 2035" (referred to as the "14th Five-Year Plan") once again emphasized making scientific and technological self-reliance a strategic pillar for national development, optimizing the allocation of scientific and technological resources, and concentrating superior resources to tackle key core technologies based on urgent national needs and long-term requirements [3]. Meanwhile, the United States, Japan, Germany, and other countries have actively conducted forward-looking research on technology forecasting and key technology selection to grasp future trends in science and technology and build national innovation systems aligned with future development [4]. These national needs demonstrate both the necessity of technology forecasting research and provide broad space for its further development.

However, with the rapid advancement of science and technology, technology forecasting activities face unprecedented challenges regarding how to effectively utilize vast amounts of information and improve the scientific and systematic nature of technology forecasting. Traditional technology forecasting primarily relied on expert wisdom, which not only had significant domain limitations but also prevented real-time updating of forecasting results. Against this backdrop, the emergence of data analytics technologies has brought new opportunities to technology forecasting research and has gradually gained high attention from governments and academia worldwide. Data-driven technology forecasting research emphasizes the use of mathematical statistics and computer science technologies to extract, mine, and reveal valuable technical information, patterns, and development laws from massive multi-source heterogeneous data [5–7]. Compared with traditional methods, this approach can help researchers maximize the use of existing data to meet the needs of multi-dimensional analysis of target technologies [8–9]. Additionally, the emergence of new methods such as natural language processing, text mining, machine learning, and deep learning can assist researchers in incorporating domain knowledge, avoiding domain limitations to some extent, and expanding the applicability of research methods.

As technology forecasting research continues to develop, scholars both domestically and internationally have conducted systematic reviews and summaries of related studies. Internationally, J. P. Martino [10] described technology forecasting methods to help researchers select more appropriate tools for different practical needs. A. L. Porter et al. [11] argued that technology futures analysis encompasses a series of concepts including technology assessment, technology foresight, and technology intelligence, and they summarized and compared the research methods involved in these studies to advance new methods for technology futures analysis. T. A. Tran and T. Daim [12] reviewed technology assessment methods and tools applied in public, commercial, and non-governmental domains. C. Lee [7] summarized the application of data analytics technologies in technology forecasting activities, addressing four questions regarding research questions, data, methods, and advantages/disadvantages. Domestically, Zhou Yuan et al. [13] provided a systematic and objective review of quantitative methods in technology forecasting and summarized the evolution of quantitative forecasting methods and research questions. Li Munan [14] analyzed research hotspots and evolution patterns in technology foresight both domestically and internationally and discussed future research directions. Wang Xuefeng et al. [15] first clarified the concept of technology forecasting, then reviewed its development history, and proposed future research prospects. Luo Wei et al. [9] organized data-driven technology forecasting research from three perspectives—data, process, and system—and identified six key technical issues requiring attention. Yuan Like et al. [4] reviewed six large-scale national technology forecasting exercises in China and analyzed the multi-level technology forecasting system and processes that China has gradually formed from perspectives including the national innovation system, technology forecasting mechanisms, and methods.

In summary, although scholars have conducted extensive reviews on technology forecasting concepts, methods, and research hotspots, the connotation and extension of technology forecasting have continuously evolved after multiple theoretical and practical changes, necessitating a new perspective to accurately characterize its generational differences. In 2014, A. D. Andersen et al. [16] pointed out that forecasting activities are undergoing a “systemic turn,” requiring more multi-source data and systematic methods to support understanding of complex logical relationships in technological innovation theory and practice [4, 8, 15], with data analytics being the most important application in technology forecasting [7]. Based on this, this study divides data-driven technology forecasting research into stages and uses bibliometric methods and knowledge mapping tools to analyze research fronts in each stage, focusing on changes in research data and methods, and explores potential future development directions by comparing differences across stages.

2. Data Sources and Research Methods

Since the late 1990s, the connotation and extension of technology forecasting have continuously expanded, with related concepts including technology intelligence, technology planning, technology assessment, technology foresight, technology opportunity analysis, technology monitoring, and technology futures analysis [17–19] (this study distinguishes technology forecasting from technology foresight; for the distinction, please refer to our previous work [15]). Considering the close connections between these concepts, we developed search strategies from two perspectives: conceptual and methodological. Conceptually, we included terms related to technology forecasting; methodologically, we covered terms related to data analytics, further limiting the scope to journals in the field of technology innovation management [12, 20].

Specifically, our data were sourced from the SCI and SSCI databases of Web of Science (WoS), using the search query: TS=(“technolog* forecast” OR ”technolog foresight” OR ”technolog monitor” OR ”technolog evolution” OR ”technolog trend analy” OR ”technolog future analy” OR ”technolog intelligen” OR ”technolog innovation pathway” OR ”technolog opportunit* analy” OR ”technolog roadmap” OR ”technolog diffusion” OR ”technolog assess” OR ”technolog evalua”) AND TS=(”pattern recognit” OR “data driven” OR “data analy” OR ”analy” OR “data min” OR ”machine learning” OR ”artificial intelligen” OR “AI” OR “text min” OR ”stochastic mod” OR “dimensionality reduction” OR “cluster” OR ”classif” OR “regress” OR ”decision tree” OR “random forest” OR ”neural network” OR “associat” OR ”support vector machine” OR ”SVM” OR ”markov model” OR ”HMM” OR ”outlier detect” OR “anomaly detect” OR ”visuali” OR “k-nearest neighbour” OR ”network analy” OR “naive bayes”) AND SO=(“IEEE Transactions on Engineering Management” OR “International Journal of Technology Management” OR “Journal of Engineering and Technology Management” OR “Journal of Product Innovation Management” OR “R&D Management” OR “Research Policy” OR “Research-Technology Management” OR “Technology Analysis and Strategic Management” OR “Technological Forecasting and Social Change” OR “Technovation” OR “Scientometrics” OR “Expert Systems with Applications”) [7]. As of September 24, 2021, we retrieved 558 papers. After manually reviewing titles and abstracts, we removed 61 irrelevant papers. The annual trend of paper publication is shown in Figure 1 [Figure 1: see original paper] (2021 data is incomplete).

Based on the stage division of data-driven technology forecasting research, this study employs the scientific text mining and visualization tool ITGInsight [21–22] to analyze literature data across four stages. We first use bibliographic coupling to identify research fronts in each stage, then apply the LinLog algorithm [23] to keyword co-occurrence networks within each front to identify research topics. By comparing and analyzing differences across stages, we explore potential future development directions for technology forecasting.

3. Technology Forecasting Development History

3.1 Stage Division

Focusing on methodological evolution, scholars have proposed various divisions of technology forecasting development history. Zhou Yuan et al. [13] divided it into four stages: (1) before 1992, when quantitative methods began to be applied; (2) 1992–2004, when quantitative-based research grew slowly; (3) 2005–2012, when it grew rapidly; and (4) 2013–2016, when it fluctuated. C. Lee [7] proposed three stages: (1) late 1940s, when qualitative and quantitative methods emerged; (2) 1960s, when related research (technology intelligence, technology assessment, technology futures analysis) proliferated; and (3) 1990s, when data volume increased and storage became more standardized, with researchers comprehensively applying mathematical statistics and computer science methods.

Building on this research and key events, this study focuses on the historical evolution of data-driven technology forecasting. Important events include: technology forecasting activities emerging in the 1940s; from the 1940s to 1960s, quantitative methods gaining importance, especially in military and aerospace sectors; and by the late 1990s, researchers realizing traditional methods could not adapt to increasingly complex social environments [24]. In the late 1990s, technology foresight became a global trend [25], with Japan, the UK, Germany, France, and other developed countries enriching the methodology system; China's technology foresight activities began with the "National Key Technology Selection Study" completed in 1992. In 2011, the Intelligence Advanced Research Projects Activity (IARPA) under the U.S. National Intelligence Council publicly launched and funded the Forecasting and Understanding from Scientific Exposition (FUSE) project, a typical technology forecasting initiative aimed at continuously mining scientific literature information across research fields and languages (primarily Chinese and English) using intelligent analysis to identify latest research trends and hotspots, with regular assessments of emerging technologies. In 2013, based on FUSE, the Forecasting Science & Technology (ForeST) project was funded. While ForeST appeared to be expert-based, it differed from traditional methods by automatically collecting questions for experts from scientific literature using text analysis and natural language processing, and intelligently selecting credible domain experts using big data and machine learning methods.

Based on the above research, events, and publication trends, this study divides technology forecasting development into four stages (see Figure 1): nascent phase (1981–1991), growth phase (1992–2010), expansion phase (2011–2017), and bottleneck phase (2018–present). The "bottleneck phase" explores intelligent technology forecasting but has not achieved substantive breakthroughs.

3.2 Research Fronts in Technology Forecasting

3.2.1 Nascent Phase (1981–1991) Given the limited number of publications and keywords in this phase, we manually reviewed paper titles and abstracts. Researchers primarily focused on "technology assessment," such as A. L. Porter et al. [26] discussing its basic characteristics and strategies; J. Nehnevajsa et al. [27] viewing risk assessment as an indispensable component; and M. W. Merkhofer [28] proposing a decision analysis-based technology assessment process including problem definition, alternative generation, deterministic analysis, probabilistic analysis, information analysis, and policy evaluation. Technology assessment emerged in the 1960s in the U.S. to evaluate technological and economic benefits of different scenarios provided by technology forecasting, assisting in selecting technologies that meet social needs and capture markets. It establishes comprehensive evaluation indicator systems to assess consequences of adopting or restricting technologies, serving enterprises, nations, and the global community at different levels. In this nascent phase, researchers began applying quantitative methods to technology forecasting, focusing on evaluating technological and economic benefits of forecasting scenarios, though research remained limited and incomplete.

3.2.2 Growth Phase (1992–2010) Using bibliographic coupling, we identified four research fronts, which through keyword clustering correspond to: (1) "Connotation and Methods of Technology Forecasting," (2) "Connotation and Methods of Technology Foresight," (3) "Technology Spillover and Diffusion," and (4) "Connotation and Identification of Disruptive Technologies" (see Figure 2 [Figure 2: see original paper]).

(1) Connotation and Methods of Technology Forecasting. Technology forecasting is conducted by innovation entities based on socio-economic development goals, using scientific principles and methods to predict and evaluate future technology development [15]. In the late 1990s, its connotation and extension continuously evolved, with more methods developed and refined [7, 13]. As shown in Figure 2(a), keywords cluster around technology forecasting and related concepts (technology intelligence, planning, assessment, foresight, opportunity analysis, monitoring), reflecting a multi-concept parallel state. Researchers emphasized objective analysis of technology trends from a systems perspective, with innovation chain, multi-path mapping, ethical/legal/social issues, strategic alignment, and strategic support systems appearing around technology assessment in Figure 2(b), confirming the focus on forecasting scheme evaluation. Innovation dynamics, open innovation, and market dynamics also emerged, validating this trend.

Methods can be categorized as exploratory, normative, or combined [18]. Exploratory methods predict future technologies based on preset curves (e.g., S-curves), focusing on objective description of future trends with minimal planning influence [29]. Figure 2(a) shows text mining, data envelopment analysis, bibliometrics, patent citation networks, and conjoint analysis as examples. Normative methods first evaluate future goals, needs, and tasks, then analyze current events to identify necessary steps and assess implementation probabilities [29], providing guidance for technology investment and human resources [30]. Common normative methods include morphology analysis, analytic hierarchy process, backcasting, and relevance trees. Combined methods leverage both approaches, such as technology roadmapping, scenario analysis, Delphi method, and nominal group technique [30]. Figure 2(b) shows "portfolio modeling" and "integrated management model," verifying the trend toward method integration [33–34].

(2) Connotation and Methods of Technology Foresight. Technology foresight typically uses technology clusters as research objects, conducting "holistic prediction" of science, technology, economy, and society, then "systematically selecting" strategic research areas and key technologies to maximize economic and social benefits through "optimal allocation," often as a national policy tool [1, 31]. Figure 2(b) shows technology clusters, technology analysis, science and technology policy, and policy research clustering around technology foresight. Methods include qualitative (e.g., scenario planning in Figure 2(b)), quantitative (e.g., extrapolation), and semi-quantitative (e.g., Delphi method, analytic hierarchy process, multi-criteria decision analysis, cross-impact analysis, technology roadmapping). As technology foresight activities matured, researchers recognized that selecting appropriate methods was key to ensuring scientific validity and effectiveness, leading to cross-method integration.

(3) Technology Spillover and Diffusion Research. Technology diffusion, defined by E. M. Rogers, is the process by which a new idea spreads from its source to ultimate adopters through channels like technology transfer and licensing [36]. Research in this phase focused on: (1) technology (knowledge) spillover and diffusion analysis based on patent citations, where citation relationships connect inventions and generate knowledge flow [37]; and (2) technology diffusion trend prediction using diffusion models like the Bass model, which predicts adopter numbers for new products/services, with patents representing technologies in the market. Figure 2(c) shows Bass model, technological learning, new product diffusion, diffusion models, Lotka-Volterra equations, and other related keywords. Technology diffusion evolved beyond simple imitation to include independent innovation based on imitation [37].

(4) Connotation and Identification of Disruptive Technologies. In 1997,

C. M. Christensen defined disruptive technology in *The Innovator's Dilemma* as technology that "typically enters from low-end or niche markets with simple, convenient, and cheap initial features, eventually replacing existing technologies, creating new markets, and forming new value systems" [40]. Subsequent academic debate focused on judging disruptive technology by its market impact. D. Constantinos, C. Gilbert, and J. Paap argued that market breakthrough innovation forms through discontinuous changes in markets, products, services, and business models, with identification criteria being whether the technology disrupts markets [41–43]. Figure 2(d) shows technological change, radical innovation, and technological discontinuities as characteristic keywords. Research focused on: (1) technology intelligence analysis for disruptive technology, where enterprises need rapid decisions on technology investment and adoption; and (2) identification of disruptive technology, though research remained exploratory without a complete systematic identification framework. For example, A. Keller et al. [44–48] proposed identification frameworks based on disruptive innovation theory and network effects, applying them to software industry cases like Google's web-based office applications versus Microsoft's desktop applications [49]. S. Hüsig et al. [48] proposed a guided interview method to assess disruptive characteristics, applying it to wireless LAN's potential disruption of mobile communication networks.

3.2.3 Expansion Phase (2011–2017) Using bibliographic coupling, we identified three research fronts corresponding to: (1) "Application of Data Mining in Technology Forecasting," (2) "Application of Technology Roadmapping in Technology Forecasting," and (3) "Application of Technology Foresight in Innovation Systems" (see Figure 3 [Figure 3: see original paper]).

(1) Application of Data Mining in Technology Forecasting. Compared to the previous phase, research methods diversified significantly, most notably with data mining applications. Data mining, or knowledge discovery, uses analytical tools to find new relationships, trends, and patterns in massive data [50], with tasks including association, clustering, classification, prediction, temporal pattern, and deviation analysis. Figure 3(a) shows text mining, data mining, patent mining, tech mining, trend monitoring, Girvan-Newman algorithm, neural networks, unsupervised learning, natural language processing, structural equation models, and structural time series models. Data characteristics evolved from structured bibliographic information to short and long texts, with emphasis on semantic analysis. SAO (Subject-Action-Object) semantic analysis emerged as a typical example, extracting technical information with subject-predicate-object structures from patents and papers, enabling analysis of short/long texts and revealing semantic relationships between technologies. Figure 3(a) shows data fusion, SAO semantic analysis, semantic technologies, and TRIZ appearing as verification. However, patent texts (structured information, titles, abstracts) remained core data, with patent analysis, patent mining, and patent classification still showing high frequency. This phase showed no obvious multi-source data fusion trend.

(2) Application of Technology Roadmapping in Technology Forecasting. Technology roadmapping is a methodology supporting industrial decision-making and long-term planning [54], first emerging in the 1970s in the U.S. automotive industry. At the national level, roadmaps identify capabilities and gaps in knowledge bases for national priority domains; at the enterprise level, they depict relationships between technology, R&D, markets, and products over time [55]. With advances in computing and databases, bibliometrics was introduced into roadmapping research. Figure 3(b) shows strong connections between bibliometrics, text mining, and technology roadmapping, with patent development patterns, tech mining, patent roadmaps, patent planning, topic analysis, text clustering, and extended map methodology appearing as keywords. For example, X. Li et al. [56] integrated bibliometrics and roadmapping for strategic planning in emerging industries, using China's dye-sensitized solar cell industry as a case. Y. Geum et al. [57] identified issues in data-driven roadmapping and proposed a technology roadmap based on association rule mining to address inter-stage relationship measurement.

(3) Application of Technology Foresight in Innovation Systems. In the growth phase, technology foresight evaluation covered three aspects: maximum benefit, maximum consensus, and optimal implementation path [35]. In the expansion phase, research focused on foresight's application in innovation systems. In 1987, C. Freeman proposed the "national innovation system" concept, describing it as a network co-constructed by public and private sectors where new technologies are initiated, introduced, improved, and disseminated through component activities and interactions [58]. Cooke [59] emphasized the importance of "regional innovation systems" for sustainable socio-economic development. Technology foresight serves as a strategic management tool supporting technology selection and strategic planning in innovation activities, while also promoting effective communication and coordination among innovation stakeholders and society. Figure 3(c) shows national innovation system, innovation policy, innovation policy governance, sustainability transitions, policy applications, open foresight, strategic foresight, collaborative foresight, and networked foresight as verification keywords.

3.2.4 Bottleneck Phase (2018–Present) Using bibliographic coupling, we identified two research fronts: (1) "Application of Topic Models in Technology Forecasting" and (2) "Intelligent Construction and Application of Technology Roadmaps" (see Figure 4 [Figure 4: see original paper]).

(1) Application of Topic Models in Technology Forecasting. Researchers focus on improved data mining methods, with topic models showing high frequency alongside bibliometrics, text mining, patent mining, tech mining, and natural language processing. The LDA (Latent Dirichlet Allocation) model [60], a three-layer Bayesian probability model, is most commonly applied. X. Han et al. [61] used LDA to identify enterprise R&D themes, construct relevance measurement models, and forecast technology trends, verifying feasibility with 3D printing. H. Liu et al. [62] developed a non-parametric topic model incorporating citations (Dirichlet process) to map complete path evolution, showing better performance than hierarchical Dirichlet processes and LDA. Research also focuses on input layer improvements using natural language processing or lexicon intervention. H. Jang et al. [63] built TechWord and TechSynset databases, showing standardized processes effectively solve technical information extraction problems. S. Kim et al. [64] proposed Word2vec-based latent semantic analysis (W2V-LSA) for better context capture in topic modeling.

(2) Intelligent Construction and Application of Technology Roadmaps. While the expansion phase introduced bibliometrics into roadmapping, the bottleneck phase focuses on big data roadmapping. Challenges lie in construction processes and result interpretation. K. Kim et al. [65] proposed a system integrating topic models and link prediction for big data roadmaps with three layers: layer mapping (topic model), content mapping (keyword network analysis), and relationship discovery (link prediction for opportunity identification), using both patent and market data. Z. A. Hao et al. [66] developed a framework based on topic models, text similarity, and technology life cycle theory for blockchain roadmapping. V. Mittal et al. [67] transformed qualitative wargaming simulation results into quantitative indicators for military roadmapping. Y. Jeong et al. [68] proposed a risk-adaptive roadmap using topic models and sentiment analysis for risk identification, keyword co-occurrence for new planning, and Bayesian networks for adaptive network topology.

4. Conclusions and Implications

Through comprehensive application of bibliometric and knowledge mapping analysis tools, this study deeply analyzes technology forecasting development from a data analytics perspective (see Figure 5 [Figure 5: see original paper]). Overall, technology forecasting has matured over decades, evolving from survey data to structured bibliographic information to short texts, with deepening data utilization. Methodologically, it has progressed from simple growth curves and analogies to data mining (natural language processing, topic models, etc.) and improved roadmapping. From a purpose perspective, it has shifted from "technology forecasting" to coexisting concepts like technology futures analysis, planning, opportunity analysis, assessment, and intelligence, then to widespread application of technology foresight in national innovation systems. However, technology forecasting does not equal technology foresight. Despite emphasizing systematic approaches for complex environments, the transition from "how technology may develop" to "how technology should develop" remains incomplete.

4.1 Building Big Data Integration Platforms for Scientific Data Sharing

Management research has traditionally been model-driven, but the data-driven paradigm (the fourth paradigm of scientific research) is increasingly advantageous for data-intensive science, exploring "unknown unknowns" from scientific data [69–70]. Many countries are promoting scientific data sharing: Singapore plans to build a data port for digital economy and society [71]; Japan centers on open data, improving websites and regulations [72]; the EU invests heavily in data ecosystems [73]; and the U.S. has developed comprehensive open data policies since 2009.

Throughout technology forecasting development, single data sources remain a major problem. Despite evolution through survey data, structured information, and short texts, patents and papers remain core data sources, accounting for 71% of research [7]. This single-source dependency affects comprehensive technology characterization. To transition from data analytics-based to data-driven forecasting, we must expand data channels, reduce acquisition difficulty, and build multi-source heterogeneous platforms integrating papers, patents, reports, social media, market information, and government data for true scientific data sharing.

4.2 Developing Intelligent Analysis Software to Reduce Scientific Data Processing Difficulty

Data analytics involves multiple disciplines (mathematics, statistics, computer science) with high technical barriers. Given researchers' backgrounds in technology innovation management, rapidly improving their data analytics capabilities to achieve the data-driven transition is challenging. While the U.S. IARPA's FUSE project aimed for data-driven forecasting and influenced methods like data mining, natural language processing, and SAO analysis [8–9], its outcomes haven't fully penetrated the technology innovation management field. Therefore, we should provide technical services (intelligent analysis software) to reduce researchers' technical burden, allowing them to focus on content and serve practical needs.

4.3 From Technology Forecasting to Technology Foresight: Leveraging Government Macro-Control

Technology foresight significantly impacts industrial policy formulation, resource allocation, structural adjustment, cluster development, and innovation system efficiency. More forward-looking and goal-oriented than technology forecasting, it shifts from "how technology may develop" to "how technology should develop." Under uncertain future risks, its goal is coordinating multi-sector government participation, multi-domain experts, and multi-regional public involvement to co-create future societal visions, systematically exploring technological value and risk across science, politics, economy, and culture to support regional development and social progress.

As summarized in the growth phase, main foresight methods include scenario analysis, trend extrapolation, Delphi method, analytic hierarchy process, multi-criteria decision analysis, cross-impact analysis, and technology roadmapping. However, in the expansion phase, while content was expanded, appropriate data and methods weren't determined. Micro-level research focuses on specific methods or single activities, while macro-level research lacks systematic method review and summary of national strategic practices.

In this context, data-driven research should emphasize not only methodological innovation but also practical service content. Government and relevant departments should fully leverage macro-control roles, organize high-quality think tank construction, promote cross-regional collaboration in technology foresight, and ultimately form multi-level foresight processes and method systems connecting enterprises, regions, and nations, enabling researchers to have rational and evidence-based frameworks and concentrating resources to build a data-driven technology foresight system.

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Author Contributions

Zhang Shuo: Drafted and revised the paper; Wang Xuefeng: Proposed the research topic and writing framework, finalized the paper; Qiao Yali: Conducted case studies, drafted and revised the paper; Liu Yuqin: Organized literature and revised the paper.

Research Status, Trends and Future Thinking of Technology Forecasting: From the Perspective of Data Analytics

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Abstract: [Purpose/Significance] From the perspective of data analytics, this paper systematically analyzes technology forecasting research based on the evolution of research data and methods. [Method/Process] To clarify its development process, this study divides data-driven technology forecasting research into four stages: nascent phase (1981–1991), growth phase (1992–2010), expansion phase (2011–2017), and bottleneck phase (2018–present), making in-depth analysis of research fronts under each stage through comprehensive use of bibliometrics and knowledge mapping tools. [Result/Conclusion] Results show that technology forecasting has been moving toward multi-level, systematic directions, but has not yet completed the leap from “how technology may develop” to “how technology should develop” in complex environments. Building scientific data sharing platforms, developing intelligent analysis software, and leveraging government macro-control will be future focus areas.

Keywords: technology forecasting; data analytics; bibliometrics; research fronts; ITGInsight

Note: Figure translations are in progress. See original paper for figures.