DSI DATA SCIENCE AND INFORMETRICS
VOL.3, NO.2, MAY. 2023

RESEARCH ARTICLE

New directions of digitally driven S&T evaluation

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ABSTRACT

Science and Technology (S&T) evaluation plays a baton role in developing science and technology innovation. However, traditional S&T evaluation indicators and methods are difficult to apply effectively in S&T evaluation practice. This paper analyzes the transformation of the S&T evaluation paradigm in the digital environment. Theories, methods, and tools of S&T evaluation research are continuously innovated and optimized; big data becomes the driving force of S&T evaluation development; the role played by S&T evaluation is shifting from a provider of statistical data and information to a participant in S&T decision-making activities. S&T evaluation research should focus on improving data retrieval and organization, knowledge mining and knowledge discovery, and intelligent evaluation models. Moreover, we suggest that scientists carry out S&T evaluation in agreement with the needs of S&T development: 1) monitoring and sensing the development of science and technology in real-time with the help of emerging digital technologies; 2) exploring solutions to major concerns such as technical project management mechanisms, utilizing advanced data science and digital technologies to identify important scientific frontiers, and leveraging big data in science of science to reveal patterns and characteristics of scientific structures and activities; 3) carrying out problem-oriented evaluation research practice focused on four aspects, including intelligent project evaluation, evaluation of the critical technology competitiveness, talent assessment, and diagnostic evaluation of the research entity competitiveness.

KEYWORDS

Digital development; S&T evaluation; Digital technology; Big Data in Science of Science; Data science

1 Introduction

Science and Technology (S&T) system is a critical piece of the society. Its fundamental purpose is to promote the development of S&T innovation and ultimately promote economic and social development. In order to improve the performance of government policies, strate-

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gies, programs, funding, universities, institutions, researchers, etc., most countries in the world need access to better and more reliable information. In particular, governments need better information on which to make their decisions to optimize material and human resources and enhance their results (McDonald & Teather, 1997). To achieve this goal, scientometricians have developed a large number of evaluation indicator systems, indices, algorithms, and models to reveal and reflect the influence, competitiveness, development level, or innovation performance of the several actors of the S&T system: scientists, research institutions, countries or regions, research projects, and technological fields from different perspectives. However, a challenge to carrying out S&T evaluation is that it is difficult to use qualitative and quantitative indicators in the evaluation practice effectively.

With the profound changes in digitalization, the development of digital technology has given rise to a new ecosystem of intelligence and digitalization. In this context, the information environment is constantly being innovated. The progress of new technologies, such as big data and Artificial Intelligence (AI), has profoundly impacted the supply of data, methods, and technologies for traditional S&T evaluation research. Digitalization is accelerating the transformation and development of the traditional paradigm of S&T evaluation research work.

2 Grasping Digital–driven Paradigm Shift in S&T evaluation

The development trend and competition pattern of science and technology in today's world are undergoing profound changes (Chen, 2022), with new technologies, such as digital technology, quantum computing, and gene editing, advancing at a rapid pace (Chen et al., 2020). The development of digital technology has become one of the critical initiatives to strive to seize the high ground in science and technology. Many countries have increased the development of digital technology to a level of national strategy; also, digital transformation has become a significant feature of major countries' current economic and social development (Chen et al., 2021). For example, in light of the current European digital transformation process, four new Horizon Europe digital calls for proposals were open for submission focusing on digital and industrial emerging technologies (European Commission, 2021). Among the challenges faced by various fields, we highlight the continuous improvement of digital governance to increase the quality of data elements and the level of digital applications.

The digital transformation has profoundly impacted the data supply, methods, and technologies for S&T evaluation work. Networking and digitalization have dramatically expanded the amount of science and technology information, which has overturned the way and means of acquiring and analyzing the data required for inherent S&T evaluation and has also significantly transformed the organization of qualitative analysis and expert consultation. S&T evaluation research needs to address the new characteristics of intelligence demand in the complex information environment and timely innovate service models and means to meet the new challenges brought by digitalization.

First, S&T evaluation research faces the challenge of handling large volumes of data, which requires the optimization and improvement of theories, methods, and tools. Scholars need to pay particular attention to the data and information supply driven by the development of big data, the method supply driven by digital technology and AI technology, and the need for improving S&T evaluation content and the organization mode driven by upgrading user needs.

With the development of scientific research theory, research results in various fields continue to be enriched. Also, the network of scholars has become more complex, and research outputs, such as journals, periodicals, patents, papers, and experimental data, have become more diverse. Professional fields are constantly expanding, and the connections and cooperation between various fields are deepening. The scale of big data in the science of science proliferates and gives rise to numerous data-driven S&T evaluation methods. For example, You et al. (2021) introduced deep learning to evaluate patent quality. Also, Ren & Zhao (2021) applied regression analysis and heuristic algorithms to patent-based technology opportunity discovery. These studies demonstrate the potential of data-driven S&T evaluation methods to effectively evaluate and discover new opportunities in real time.

To address the challenges of handling large volumes of data, it is essential to continue optimizing and improving theories, methods, and tools to enable efficient and effective S&T evaluation.

Second, data has become an important production factor in the digital society, which is valid for S&T evaluation. As it was previously mentioned, S&T evaluation needs the development of data science. It includes systematically understanding data science, improving the theoretical systems, promoting methodological innovation, and expanding application practice (Chao et al., 2022). Data science comprehensively uses methods such as math, statistics, programming, AI, and Machine Learning (ML), to uncover internal hidden information in data (IBM, 2022). S&T evaluation needs to improve the storage, indexing, and knowledge organization capacity of massive big data, significantly strengthen the construction of professional field databases, and form a critical infrastructure to support S&T evaluation research. Additionally, we need to continuously improve the mining and computing capacity for these rich multi-source data and fully integrate with AI, deep learning and other technologies to achieve intelligent analysis and intelligent evaluation service paradigm upgrade.

Finally, the development of digital technology has dramatically enriched the access to information for users of S&T evaluation services, such as science and technology managers and researchers. At present, S&T evaluation services can no longer meet the needs of users by providing conventional data statistics and information analysis alone. The science and technology community needs S&T evaluation institutions to play a think tank and decision-making advisory role. And S&T evaluation is not just a provider of statistical data and information but also a participant in science and technology decision-making activities. Consequently, policymakers need deep insights into the science and technology activities to guide decision-making and strategic planning, not raw or basic statistics.

In this sense, intelligence is becoming one of the important trends of think tanks, which are using digital technologies such as AI and ML to store and train the data and information, research methods, and cases involved in think tank research so that think tank research platforms can shift from passive storage to active proposal (Pan et al., 2021). Think Tanks research tends to use big data to create and analyze computational metrics and uses data envelopment analysis, cluster analysis, principal component analysis, regression analysis, and other methods to analyze the data (Pan et al., 2021). For example, RAND Corporation uses the AI model fuzzy cognitive maps (FCM) to study the factors that promote or inhibit public support for insurgency and terrorism (Osoba & Davis, 2019). National Institute of Science and Technology Policy (NISTEP) of Japan has combined word embedding techniques with citation analysis to measure novelty in science and technology literature based on the assumption that a paper is novel if it cites a combination of semantically distant citations

(Shibayama et al., 2021). Additionally, the Austrian Institute of Technology has used numerical techniques, such as text mining, clustering, and association rule extraction (ARE), to establish innovativeness indicators to assess the novelty of research projects (DBF, 2017).

Overall, digital technologies such as AI and ML in S&T evaluation research allow for the creation and analysis of computational metrics and the development of effective methods for behavior modeling and simulation. This enables S&T evaluation institutions to play a think tank and decision-making advisory role and provide policymakers with deep insights into science and technology activities to guide decision-making and strategic planning.

3 Studying S&T Evaluation Methods Aligned with the Digital Requirements

The progress of digital technology has extensively promoted the evolution of S&T evaluation research methods. To keep up with the requirements of digital development trends, the primary task of S&T evaluation research work is to gradually build a more comprehensive evaluation architecture with the help of open-source big data, AI and other technologies and then form the theoretical basis for conducting high-level S&T evaluation research and services. Furthermore, we can provide high-quality open-source intelligence support and consulting services for governments, enterprises, universities, research institutes, and others (Zhao et al., 2022). At present and for a time in the future, S&T evaluation research should focus on enhancing the following methodological capabilities.

3.1 Data retrieval and organization methods

The development of digital technology has brought about a dramatic expansion of data, and the open access movement has driven a tremendous increase in data accessibility, resulting in more diverse data types and data structures, which include structured data, such as not only publications or patents data, but also social media, blog or customer data, and unstructured data like audios, videos, pictures, etc. Both structured and unstructured data should be collected efficiently and completely using many methods, including manual entry, web scraping, and real-time streaming data from systems and devices.

The explosive growth of data has placed higher demands on the accuracy of information retrieval. In order to capture the semantic information of search terms, instead of simply matching the search terms with the full-text index of data on the Internet, we can construct a knowledge graph to provide intelligent distributed information retrieval from multiple data sources. GSim is a knowledge graph-based information search algorithm that proposes a semantic similarity model with an implicit feedback correction mechanism. The metric of keyword similarity integrates semantic information and statistical information in the knowledge graph, and it can find the most relevant approximate matches by mining the intrinsic relationships between entities that do not have perfect matches, improving the accuracy of information search in terms of both recall and precision (Li et al., 2021).

Furthermore, clustering combined with pattern mining can also be used to improve the accuracy of information retrieval. Cluster-based Retrieval using Pattern Mining (CRPM) divides the object database into clusters, performs pattern mining algorithms on each cluster to build a pattern base, and then ranks the clusters using Weighted Terms in Clusters (WTC) and Score Pattern Computing (SPC), thereby reducing time complexity while improving the accuracy of the returned objects (Djenouri et al., 2021).

Data fusion and organization present more complex challenges when dealing with diverse data types from varied sources. Researchers need to preprocess multi-source data, including cleaning, indexing, deduplication, and correlation, and then store it in a standardized and structured way as a high-quality information foundation for subsequent data analysis and evaluation research. Ontology is a cross-domain knowledge organization model. Zhou et al. (2021) proposed a real-time ontology RTO model, which keeps only the entities related to user requirements in the domain ontology. RTO is lightweight, avoiding the problems of large scale and low matching efficiency of super large ontology (SLO) and the difficulty of maintaining and updating top-level ontology (TLO). It is constructed by searching domain ontologies related to the set of domain terms and generating filters, and then extracting and integrating sub-ontologies based on the filters. Compared with SLO and TLO, RTO improves the accuracy and efficiency of ontology association.

In addition, the extraction of information and knowledge from unstructured data such as natural language text and pulse signals can benefit from advanced algorithms such as deep convolutional neural networks (DCNN). Natural language text is one of the primary forms of unstructured data, and it is crucial to extract knowledge from massive text data. Banerjee et al. (2021) proposed a novel trainable and integrated Natural Language Information Interpretation and Representation System (NLIIRS), which extracts information from natural language sentences by an improved Named Entity Recognition algorithm, converts them into structured and well-organized information, i.e., tuples of relational tables, and avoids the time-consuming lexical annotation process. Also, the system converts natural language queries into structured query language (SQL) and then extracts valuable information from the above relational tables. In the medical field, pulse signals contain rich information about the state of the cardiovascular system, which is also unstructured data. In the study of pulse type prediction, a DCNN kernel can extract the unstructured data's local features (Yan et al., 2021). Compared with the time domain and frequency domain features alone, the average accuracy of the DCNN- and SVM-based stacking network (DSSN) pulse signal ensemble classification model, which incorporates the unstructured data of pulse signals, is significantly improved.

In short, in the digital environment, S&T evaluation cannot be limited to simple data retrieval methods and single data sources. Instead, it should integrate multi-source data from technology, industry, market, public opinion, and other domains and improve continuously data retrieval algorithms to enhance precision and recall. Additionally, based on the advancements in digital technology, data fusion and organization methods should be improved to establish a foundation for the subsequent knowledge discovery and S&T evaluation systems.

3.2 Knowledge mining and knowledge discovery methods

The analysis of rich, heterogeneous data requires advanced techniques such as heterogeneous data association analysis, data mining and knowledge discovery methods, and other related methods. The value of data-driven knowledge discovery analysis is the following aspects: it can reveal deeper information and knowledge behind the data, promote the integration of knowledge in the whole process of scientific research, guide the cross-fertilization of disciplines, and provide new ideas and new means for S&T evaluation research.

To achieve these goals, it is essential to promote the use of AI technology, such as semantic relationship mining and knowledge extraction, to enhance data statistics, association analysis, and knowledge discovery capabilities. Data scientists can use abundant data to conduct exploratory analysis to investigate scientific activity patterns, output distributions, and causal relationships. Typical digital approaches include ML, deep learning, etc.

For example, Mishra et al. (2021) proposed a technique that uses ML classifiers, such as logistic regression, multilayer perceptron, random forest, and deep learning networks, such as long short-term memory (LSTM) and convolutional neural network (CNN), to automatically identify problem and solution strings from large amounts of unstructured textual data such as journals, literature, and newspapers. The authors found that the CNN approach gave the best classification results, demonstrating the potential of AI for automatically identifying solutions to problems.

Additionally, Chen et al. (2021) proposed a structure-function knowledge (SFK) extraction method for bionic design. This method uses dependency syntax analysis to define six types of dependencies and identify potential structural knowledge (SK) and functional knowledge (FK). Domain-related topics are then extracted using keyword extraction, which is used to filter out unrelated knowledge. Finally, structures and functions with associated relationships are combined into SFK. The SFK extraction can help designers quickly discover the required biological information and solutions to problems.

AI can also be used to predict reliable scientific facts from the literature and improve the replicability of scientific experiments (Belikov et al., 2022). Taking gene regulatory interactions as an example, Belikov et al. (2022) predict the existence of gene interactions in high-throughput experiments based on their position in the gene interaction network and then use Bayesian algorithms to infer the direction of each gene regulatory interaction to obtain when a gene interaction is neutral (non-existent), positive or negative. The prediction of gene regulatory interactions can help scientific institutions increase reliable scientific knowledge, guide the development of new experiments, and promote scientific progress.

In conclusion, the application of AI has great potential to accelerate knowledge mining and knowledge discovery. By continuing to explore and innovate with these technologies, we can better utilize data to uncover new insights, develop new solutions, and advance S&T evaluation progress.

3.3 Intelligent evaluation methods and models

Researchers need to study intelligent evaluation indices, indicators and models based on AI and big data, integrate scientific, technological and industrial multi-data, construct a new structured S&T evaluation index system, and provide an effective method for scientifically carrying out the evaluation of several processes and actors (i.e., countries, institutions, talents, projects, achievements, and technologies).

The S&T evaluation methods and models are constantly improving to keep up with the rapidly developing field and a large amount of scientific data. To evaluate the industrialization of S&T achievements, Chang et al. (2021) established an evaluation index system and used FAHP to determine the weights of influencing factors for the pre-evaluation of local industrialization of S&T achievements. Li et al. (2022) combined fuzzy comprehensive evaluation (FCE) and hierarchical analysis to construct evaluation indexes for the transformation of S&T achievements. Yin et al. (2022) proposed an intelligent evaluation method for the scientific research ability of college students by constructing an evaluation index system based on scientific cognitive ability, scientific practical ability, scientific innovation ability, and university research environment and then designing the weights of evaluation indexes. They then used the BP neural network model and the chaotic sine-cosine grasshopper optimization algorithm (CSCGOA) to determine the weights and thresholds of the BP neural network to predict the research ability of college students comprehensively based on internal and external influencing factors.

In conclusion, the development trends of intelligent S&T evaluation models include more accurate prediction capabilities, more comprehensive data integration, and more automated evaluation processes. Researchers need continuous improvement and intelligence of S&T evaluation methods and models to better evaluate scientistic processes and actors, providing better guidance and support for scientific innovation and development.

4 Carrying out S&T evaluation in line with the technology development

The essential task of S&T evaluation is to meet the needs of S&T development, which requires making positive contributions in supporting the strategic decision-making process of policymakers and ultimately promoting S&T progress. The rapid progress of digital technology also stimulates the iterative upgrading of S&T evaluation theories and methods, which requires S&T evaluation work to strengthen data science research and to expand the evaluation methods and tools utilizing AI, ML and semantic representation. Only then can it comply with the nutritional development needs of China's science and technology innovation system, providing practical solutions to decision-making and consulting problems. The evaluation results integrate multi-dimensional social and economic development perspectives, guiding strategic, professional, comprehensive and forward-looking decision-making activities.

4.1 Monitoring and Sensing S&T Development

With the assistance of emerging digital technologies, we can carry out structured and long-period monitoring and sensing of global science and technology development in real-time and present the latest progress and situation of global science and technology innovation. A web crawler (Li, 2005) is a vital tool to obtain real-time web information resources and monitor science and technology dynamics, essentially a program that automatically crawls web content. It starts from one or more initial seed URLs, obtains the IP addresses corresponding to the URLs by querying DNS servers, and then obtains the pages corresponding to the specified IPs through HTTP request commands. Subsequently, it processes the pages for purification, filtering and data extraction, labeling, and conversion to obtain the required information. The web crawler continuously extracts the URLs in the current page, puts them into the URL queue to be crawled after filtering out irrelevant URLs, and then extracts a new URL from the URL queue to be crawled and repeats the above until the termination conditions are met.

With the massive growth of dynamic web pages, monitoring and sensing global technological developments demands to access to real-time, high-quality data from multiple databases, which requires information collection from deep web databases. Some databases define an entry page for collectors to collect information from the databases through web links. In contrast, we need to get real-time data updates for other databases through the observer pattern and query triggered crawling (QTC) (Wu et al., 2008).

Currently, several institutions are implementing real-time monitoring and sensing of sci ence and technology development trends. The Service Cloud for Strategic S&T Information Monitoring (Zhang et al., 2014), developed by the National Science Library of CAS, is aimed at S&T intelligence personnel and S&T decision-makers. Based on the websites of domestic and foreign institutions in different science and technology fields, the system realizes several methods (i.e., automatic monitoring and collection, information extraction, automatic labeling, automatic classification, automatic abstraction, text mining, entity extraction, and others) to calculate the value of science and technology resources, identify the critical S&T objects, S&T terms, and research hotspots contained in science and technology resources, grasp the development profile of each science and technology field, and facilitate science and technology decision-making.

The decision theater built by the Institute of Scientific and Technical Information of China (ISTIC) is an intelligent and interactive S&T policy decision-making platform based on S&T information big data. It provides a visual and intuitive integrated display space to participants such as decision-makers, domain experts and IT experts through real-time data, intelligent models, interactive visualization and virtual reality technologies, helping them to make sandbox projections, perform simulation forecasts and simulate decision effects (Zhao et al., 2020).

4.2 Future–oriented S&T evaluation

The core of S&T evaluation work is to promote the development of science and technology innovation. Therefore, research should focus on technology strategies, scientific issues, and the topic selections in cutting-edge fields and directions, and also accurately identify the direction of technological breakthroughs, as well as significant frontier scientific issues. Specifically, it is manifested in the following three aspects.

4.2.1 Reveal the field´s development trends and explore solutions for major concerns

Reveal the field's development trend and explore solutions to major concerns based on the external characteristic analysis of scientific research outputs such as policies, plans, strategies, actions, fund grants, papers, and patents. For example, basic research is the source of the whole science and technology innovation system. Deepening the research on basic research strategic policy needs to focus on six principles: foresight, guidance, operability, specialization, linearity and feasibility. As China advances into more uncharted territories in science and technology, it is necessary to explore more global frontier issues, where uncertainties and unknowns are significantly increased. China needs to adopt a new management mechanism to carry out non-consensus or disruptive project research, and continue to research and optimize decision-making methods and models, explore flexible process management methods, and accelerate breakthroughs in cutting-edge innovation by providing funding.

The organizational mechanism of scientific plans and technology projects needs to focus on scientific establishment and management methods of strategic technology projects that have long cycles, high risks, high difficulty, and good prospects; explore flexible and effective operating mechanisms for new project funding models such as "open competition" and "horse racing"; study and develop management methods for non-consensus or disruptive projects; and establish a sustainable and stable mechanism for establishing and assessing basic research projects, especially the selection mechanism for free exploratory and purely basic research topics should be clarified.

4.2.2 Identify important S&T frontier directions and judge the future direction of S&T fron-

tier development relying on advanced data science and digital technology

The discovery of new scientific problems and the judgment of future S&T development directions not only put forward higher requirements for scientists in specialized fields but also bring new opportunities and challenges to the S&T evaluation work. Scientists in the S&T evaluation field need to answer whether new scientific problems and future S&T directions are identifiable and foreseeable, and which intelligence analysis methods would be used to identify and foresee the work.

In recent years, the technology intelligence community has shown increasing interest in the identification and prediction of frontier, emerging, hot, and disruptive technologies. Numerous academic achievements and research reports have been published in this area. For example, Science magazine has published the annual top 10 scientific breakthroughs recently, introducing the latest breakthroughs in global science and technology development (Science, 2021). Chinese Academy of Sciences and Clarivate have also continued to publish annual research frontier reports by studying the citation patterns and cluster analysis of papers (CASISD, 2021).

Through the existing studies, we find that the identification methods of these technologies still have the problems of vagueness and unclear boundaries. Sorting out from the conceptual definition of these technologies, it can be seen that once the importance of the technologies is determined or discovered, we can understand the fundamental relationship among them as follows: disruptive technologies belong to frontier technologies, frontier technologies partially overlap with emerging technologies, and their commonality is both hot technologies. However, in the early stages before these technologies are discovered or identified, technology identification is challenging: emerging technologies and frontier technologies are difficult to discover before they become hot technologies; disruptive technologies may already be frontier, emerging, or hot technologies or even common technologies. After being confirmed, disruptive technologies can be classified as frontier technologies, but not all frontier technologies are disruptive technologies. Recognizing these basic logical relationships is a fundamental prerequisite for effective research on technology identification.

The hope to predict new scientific developments exists today in practically all areas of modern science, such as knowing in advance what discoveries will be made, by whom, when and where. In technical prediction, earlier research was dominated by peer review and the Delphi technique. However, in the field of library and information science, researchers expect to use big data in science of science to produce more objective and accurate predictions than experts' qualitative predictions.

However, the exponential growth of big data in science of science is rapidly increasing the demand for analytical methods and tools. Traditional statistical and analytical metrics, algorithms and models are no longer able to meet the new research needs. Especially in technology identification and prediction research methods, there are only so many fully reliable and effective methods and tools. In order to solve this bottleneck, it is necessary to build a scientific and feasible theoretical framework system and a methodological system to propose practical algorithms or models. Also, researchers should develop open-source standardized tools and platforms for users to use widely and upgrade the usefulness of tools continuously. ML and AI methods have become increasingly widespread in recent years. For example, Zhou et al. (2020) used data augmentation and deep learning techniques to predict emerging technologies based on proprietary data. The empirical prediction results of this study on Garter's technology maturity curve showed that the method had 77% accuracy.

4.2.3 Reveal the laws and characteristics of the scientific structure and scientific activity based on big data in science of science

The value of big data in science of science (Chen & Cao, 2020; Chen et al., 2022) research is that it can reveal the more profound information and knowledge behind the data and provide new ideas and means for S&T evaluation research. The analysis of big data in science of science has greatly expanded the effectiveness of S&T evaluation, mainly in the following three aspects.

First, based on big data in science of science, the inherent laws and characteristics of scientific research can be revealed and depicted, such as revealing the birth and evolution process of disciplinary directions, mining the laws of scientific research activities and innovation, etc., which helps to understand the factors affecting the development of science from the perspective of the whole scientific research process. It can promote the development of technology management and R&D organizational behavior into a better direction. For example, Wu et al. (2019) found that small teams have more potential to make disruptive innovations, which suggests that science and technology innovation activities require multiple organizational models, and that supporting multiple forms of research organization mechanisms needs to be considered in the process of formulating science and technology policy and conducting research funding.

Second, the scientific structure can be analyzed based on the internal relationships of big data in science of science. In 2005, Boyack et al. (2005) produced a domain-wide map of scientific structure based on more than 1000,000 journal articles from more than 7,000 journals in the natural and social science field, which can be used to detect correlations between disciplines. Especially in recent years, with the development of digital technologies, network analysis methods and information visualization methods, researchers can parse and identify the inherent and objective scientific structural features based on the external characteristics of big data in science of science (Wei & Wei, 2011). Of course, most current scientific structure analyses are based on collaborative or referential networks, but there is yet to be a clear theoretical basis for the choice. Also, there is a need for continued research on the construction of networks, and the question - of what kind of networks are effective in revealing scientific structure - also has yet to be a precise answer.

Third, we can reveal the organizational operation patterns of research teams or institutions by analyzing data on research outputs, scientists' education and careers, and extracting common knowledge of research activities, which is of great value for guiding the construction of research teams, and also talents’ introduction and training. For example, studies have found that early to mid-career is more likely to produce the best scientific discoveries or scientific results for individual scientists (Jones & Weinberg, 2011).

4.3 Conducting problem-oriented evaluation research practice

With the initial intention of promoting the development of science and technology through S&T evaluation (Chen & Zhang, 2020), based on the innovation brought by digital technology to the evaluation theory and methods, S&T evaluation practice should focus on the following four major issues.

4.3.1 Carry out project evaluation and performance assessment based on an intelligent project management system

The rapid advancement of digitalization and informatization in scientific research management has expanded the space for S&T evaluation scientists to participate systematically in project review and performance evaluation. Scientists can directly guide the project establishment and review based on research results on scientific structure analysis, significant scientific problem discovery, technology hotspots and frontier direction identification, and disruptive technology prediction, which will help improve the rationality of project goal setting and the scientific nature of implementation plans. For project performance assessment, advanced digital technology tools can improve the ability to evaluate the performance of project results and reveal the scientific value, technical value, and economic value of the results at an in-depth semantic level rather than being limited to quantitative assessment with the quantitative indicators identified in the mission objectives.

4.3.2 Organize critical technology competitiveness level evaluation

International technological competition is a competition within the entire technology innovation system, including technology systems, talents, technologies, standards, etc. The most intuitive external manifestation among them is the competition for core technologies. However, most of the current evaluation work on the crucial technology competitiveness remains at the level of quantitative comparative analysis of scientific and technological achievements such as papers or patents, and relatively little research work goes deeper into the intrinsic competitiveness of core technologies, which is due to the lack of effective methods. So the continuous innovation of digital-driven methods is urgently needed. In particular, S&T evaluation workers should comprehensively utilize multidimensional evaluation strategies such as disciplinary structure, age structure, and research paradigm of relevant scientific research entities, and combine economic benefits, industrial value and other indicators to improve the objectivity of the critical technology competitiveness analysis.

4.3.3 Refine the discovery and effectiveness assessment of outstanding talents

Carrying out evaluation work for talents should be based on the basic orientation of discovering various types and levels of talents rather than going for a general ranking of scientific researchers. Talent evaluation needs to discover the irreplaceable and unique value of each scientist rather than comparing the superiority of one to the other horizontally, thus maximizing the innovation potential of all talents. S&T evaluation researchers should systematically analyze the growth rules, discovery, and cultivation mechanisms of strategic scientists and leading talents, investigate the cultivation programs of outstanding young talents, study the cultivation mechanisms of high-level innovation teams, and even analyze the long-cycle talent cultivation system that starts at the secondary school stage, and also explore the all-round system of introducing, cultivating and employing scientific talents. Researchers should try to build methods and models for discovering strategic scientists, leading talents, high-level talents and outstanding young scientists, developing implementation paths for breeding scientific masters, and studying evaluation methods for the unique value of talents.

4.3.4 Utilize multi-dimensional digital information fully to observe the competitive ability and level of countries, regions, and institutions

The current mainstream work on the competitiveness evaluation of countries, regions, cities, and scientific institutions relies highly on quantitative indicators, such as economic and industrial data, journal papers, or patents, which are mostly "revealing" indicators. However, what the evaluation target truly needs is a "diagnostic" evaluation, which takes revealing its strengths and weaknesses as the starting point, proposes diagnostic improvement suggestions, and ultimately enhances its practical competitiveness. S&T evaluation workers must study evaluation indexes that combine long and short cycles, macro and micro, qualitative and quantitative, and explore the theoretical basis of index systems that can reveal the R&D

layout and competitiveness of universities, research institutes, enterprises, etc., and ultimately build a feasible diagnostic evaluation index system.

5 Conclusions

This paper describes the development direction of digitally driven S&T evaluation research from three aspects: S&T evaluation paradigm, intelligent evaluation methods, and S&T development needs. The rapid growth in the scale of big data in science of science and the more diverse data types have led to a change in the paradigm of S&T evaluation. Digital technologies, such as knowledge mapping, deep learning, heuristic optimization algorithms, natural language processing, and social networks, have been innovatively applied to S&T evaluation work, yielding good results. However, there are still limitations in S&T evaluation research. S&T evaluation researchers should integrate multi-source data, improve data retrieval and storage efficiency, develop the fusion and organization technology of heterogeneous data, improve the knowledge extraction and mining ability, and construct intelligent and systematic S&T evaluation index system and evaluation methods. S&T evaluation work needs to make full use of the opportunities brought by the development of digital technology, monitor research dynamics in real-time, face future development strategies, and carry out problem-oriented evaluation research practices.

In conclusion, the transformation to intelligence and digitalization has become a significant trend in developing S&T evaluation. In this regard, S&T evaluation research should not be limited to data statistics and expert experience. However, it should rely on the construction and improvement of big data in science of science, integrate multiple information such as science, technology, economy and industry, and build intelligent, real-time, decision-oriented, and future-oriented evaluation methods and models. Focusing on scientific issues such as in-depth semantic level project evaluation, intrinsic competitiveness of core technologies, development characteristics and potential exploitation of talents, and "diagnostic" evaluation of scientific research entities, S&T evaluation should lay a solid foundation for the healthy development of science and technology in the future, which is of strategic significance to the long-term development of the country.

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