Technological Forecasting & Social Change 130 (2018) 165–176

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

A technology delivery system for characterizing the supply side of technology emergence: Illustrated for Big Data & Analytics

Ying Huang[a], Alan L. Porter[b,c], Scott W. Cunningham[d], Douglas K.R. Robinson[e], Jianhua Liu[f], Donghua Zhu[a,*]

[a] School of Management and Economics, Beijing Institute of Technology, Beijing 100081, China
[b] School of Public Policy, Georgia Institute of Technology, Atlanta, GA 30332, United States
[c] Search Technology, Inc., Norcross, GA 30092, United States
[d] Faculty of Technology, Policy and Management, Delft University of Technology, Jaffalaan 5, 2628 BX Delft, Netherlands
[e] Laboratoire Interdisciplinaire Sciences Innovations Sociétés (UMR-LISIS), CNRS-IFRIS, Université de Paris-Est, Paris, France
[f] National Science Library, Chinese Academy of Sciences, Beijing 100190, China

ARTICLE INFO

Keywords:
Technology delivery system
Tech mining
Emerging technology
Big Data
Technology assessment
Impact assessment

ABSTRACT

While there is a general recognition that breakthrough innovation is non-linear and requires an alignment between producers (supply) and users (demand), there is still a need for strategic intelligence about the emerging supply chains of new technological innovations. This technology delivery system (TDS) is an updated form of the TDS model and provides a promising chain-link approach to the supply side of innovation. Building on early research into supply-side TDS studies, we present a systematic approach to building a TDS model that includes four phases: (1) identifying the macroeconomic and policy environment, including market competition, financial investment, and industrial policy; (2) specifying the key public and private institutions; (3) addressing the core technical complements and their owners, then tracing their interactions through information linkages and technology transfers; and (4) depicting the market prospects and evaluating the potential profound influences on technological change and social developments. Our TDS methodology is illustrated using the field of Big Data & Analytics ("BDA").

1. Introduction

One can view technology development from a number of perspectives. The supply chain perspective views technology development as an attempt to deliver a system to meet specific human needs or wants, while the market embedding perspective looks at technology development in terms of uptake, adoption, and the wider use of technology. Through this perspective, innovation is strongly affected by the dynamics of the economic and the social/political contexts that shape the transformation of new technology into products and services that are well embedded in markets and society. Both perspectives are techno-centric, in that they start with a technology option and explore the future pathways of development and uptake.[1] When facing constantly fluctuating economic environments and swiftly changing markets, industrial actors are driven to pursue continual technological innovation as a response to maintaining a competitive edge (Wang et al., 2008). However, the process of technological innovation, which takes place through highly complex socio-techno-economic systems, is marked by the increasing role played by other factors, such as regulation and marketing. The social acceptability of innovation, especially where organized critical groups are concerned, must also be considered (Giget, 1997). Addressing these important relationships in the process of socio-technical change associated with complex technologies, thus, becomes a thorny problem for decision makers, both in government and industry.

Over the past few decades, a large number of innovation system approaches to explicate innovation in complex competitive environments have emerged. We have found the "Technology Delivery System (TDS)" conceptual model, first proposed in the 1970s, offers a helpful techno-centric approach for understanding what translates an idea into

* Corresponding author.
E-mail address: zhudh_bit@163.com (D. Zhu).

[1] This is the opposite of a user-centered perspective, which places the user at the center, and where many technology options are compared and contrasted based on user-defined criteria.

http://dx.doi.org/10.1016/j.techfore.2017.09.012
Received 1 February 2017; Received in revised form 25 August 2017; Accepted 12 September 2017
Available online 20 September 2017

an effective innovation.[2] The TDS offers an important framework for gathering and organizing information, and for drawing conclusions about the implications that can be used for decisions around emerging *technology supply chains*.[3] It also helps those involved in technological forecasting to organize and communicate the critical problem-structuring phase of a forecast (Roper et al., 2011). The resulting system model can help public and private sector decision makers grasp key structures and processes and how these can be tuned to enhance the prospects of successful innovation.

Until now, we have not formulated a systematic approach to understand the new and emerging science and technology (NEST) and its associated TDS modeling, including technological regimes, technology architectures, and socio-technical systems (Porter et al., 2015). This paper presents a systematic framework for building a TDS model to explore empirical insights that draws upon different types of documents (e.g., policy reports, funding proposals, scientific articles, and patent assignment information).

The remainder of this article is organized as follows: following this introduction, the theoretical background of this study and a short overview of related literature is provided in Section 2. Section 3 explores the research objectives; then the systematic approach of building a TDS framework is developed in Section 4. Section 5 describes the search strategy and data retrieval for the present case analysis, leading into Section 6, which presents the empirical results of the Big Data & Analytics ("BDA") case study. This is followed by a discussion and the managerial implications in Section 7. Finally, our conclusions are drawn in Section 8.

2. Literature review

The notion of a TDS was employed by the National Academy of Engineering to represent the complex processes by which knowledge of the consumer is deliberately applied to achieve amenities and social values (Wenk, 1973). In this model, the innovative process is driven by the market, where the government attempts to minimize the barriers that impede the TDS and to support struggling industries through an innovation policy of fixing market failures (Branscomb, 1973).[4] Each technology has its own delivery system, consisting of a number of interactive components, and each component consists of a set of institutions that contribute to a common function. These institutions might include research institutions, manufacturing firms, product distribution companies, or the lending institutions that make operating funds available to other components in the TDS (Ezra, 1975). Wenk and Kuehn (Wenk and Kuehn, 1977) proposed a TDS framework that included four elements (input, public and private institutions, intermediary institutions, and outcomes) to project the important factors involved in a particular innovation. The TDS approach strives to address the most important relationships in the process of dynamic socio-technical change in order to reflect the ongoing process of technological development. The TDS depicts the innovation process as a stream of activities, driven by the invention of new capabilities and pulled by the demand for products, and the process is greatly influenced by a variety of exogenous societal influences, such as government policy (Porter et al., 1985).

The National Academy of Engineering report was innovative for its time. However, it has now become abundantly clear that actors and stakeholders play a central role in the delivery of new technology. Two prominent sources soon set out the fundaments of a new discipline of stakeholder analysis and management (Freeman, 1984; Mitroff, 1983). Sources such as these helped educate subsequent generations of engineers and engineering management. Other developments focused on the right delivery of technical analyses. Analysts soon asked whether a single correct solution to technical problems could be delivered at all – when the very definition of correct is something that can be contested (Rittel and Webber, 1973). This led to new forms of operational research addressing both the "hard" and "soft" sides of a problem. The field is now more correctly known as problem structuring methods (Rosenhead and Mingers, 2001). References such as these were so persuasive and so central to thinking about engineering problems that they arguably helped launch the new fields of engineering management and technology management (Cunningham and Kwakkel, 2011).

Despite the widespread influence of thinking about actors, stakeholders, and socially contested problem solving in engineering, a question remains: How can we best update the National Academy of Engineering report on TDS to take this well-established knowledge base of engineering and technology management into account? This is a much more specific question, as we can now focus specifically on the needs and requirements of the TDS and its users. After reviewing a dozen distinct strands of literature, a question arises as to whether there is something uniquely useful about the TDS concept. The purpose of this review is to overview a number of potentially relevant and closely-related concepts regarding TDS modeling. This review and synthesis seeks to generate a clearer perspective regarding the strengths, weaknesses, limitations, and future opportunities for research into TDS. We divided the literature into three parts – perspectives on technology, perspectives on delivery, and perspectives on systems.

The technology perspective emphasizes the R & D processes required to produce a new technology. A key contribution is technology roadmapping (TRM). According to Phaal et al. (Phaal et al., 2004), a technology roadmap helps organizations reconcile the technological and commercial perspectives on the emergence of new technology. These authors identify eight distinct kinds of maps, developed for eight different kinds of organizational purposes. Kappel (Kappel, 2001) provides further direct evidence of how technology roadmaps promote useful strategic conversations inside a technology-driven organization. TRM became important for guiding large R & D consortia, particularly those surrounding the development of semiconductor technologies.[5] Walsh (Walsh, 2004) provides a useful modern case study demonstrating the continued relevance of roadmapping for the newest generation of semiconductor technologies. The technology roadmapping perspective is most widely cited in the fields of management and business.

The "delivery" notion focuses attention on the complex network of organizations, policies, and incentives that help produce and deliver technology-based products or services. This perspective is largely adopted in the social sciences literature, including the fields of sociology and public administration. The policy analysis framework emphasizes a feedback loop between perceived gaps in policy and strategy, and the measures taken to enact desirable changes in a system (Walker et al., 2001). Prominent within these theories is the concept of a small coalition of actors who negotiate with each other in pursuit of specific policies or economic interests. Representative theories include advocacy coalition theory and growth coalition theory (Sabatier, 1988;

[2] The authors acknowledge that user-centered approaches are also useful, but for those strategically interested in particular technology fields, a techno-centric approach is very useful even though one has to be aware that it is only one perspective on technological innovation.

[3] The TDS focuses on supply chain activities rather than the whole socio-technical system of a particular innovation. Thus, while other areas of the socio-technical system are important (for example, user uptake processes), these are not the focus. However, users do become involved in supply chain activities and so are included in the TDS, but only in their role as influencing supply-chain activities not in their role as adopters of a technology option.

[4] The role of governments in Western capitalism has come into question, where the role of governments solely to fix market failures, rather than direct markets, is being reconsidered. For a very recent work, see http://esamultimedia.esa.int/docs/business_with_esa/Mazzucato_Robinson_Market_creation_and_ESA.pdf.

[5] Some authors have argued that these consortia were necessary for industrial coordination given the lack of a centralized industrial policy in the United States (Saxenian, 1990).

Zhu, 1999). Triple helix theory addresses the collective roles of three actors in the production of technology – government, industry, and academia (Etzkowitz and Leydesdorff, 2000). Opportunity structure theory describes the political environments where large, and often formless, social movements can nonetheless find traction (Kitschelt, 1986). Strategic niche management (Kemp et al., 1998) provides equivalent advice for small companies involved in breakthrough technology fields, which must find their position despite the epochal change associated with a technology transition. Another two approaches associated with the delivery perspective on TDSs are stakeholder analysis methods (Bryson, 2004) and actor-network theory (Bryson et al., 2009; Latour, 2005). Stakeholder analysis techniques provide a host of practical and graphical methods for pursuing “implicit theories of policy making”. Actor-network theory traces associations between social groups and physical objects, explaining how these associations grow more stable and more legitimate over time. A particularly interesting “child” of actor-network theory is techno-economic networks (Callon, 1990; Callon et al., 1992). In this approach, actor-network theory is used to chart the network of actors and systems around four poles (research, technology production, finance, and governance/regulation), where the actors, artifacts and elements linking these objects constitute a network – something like a bespoke TDS for each individual project. The stability, change, and transitions in socio-technical systems are interpreted between nested levels (niche, regime, landscape) through a multi-level perspective (MLP) framework, and the spatial dimension is treated as a relational scale, constituted by networks of actors across different territories (Raven et al., 2012). Socio-technical networks and techno-economic networks can be at the individual project level (micro) or at the level of industries (*meso*) – one reason it is mentioned in both the delivery and systems columns of Table 1 (Green et al., 1999).

The final perspective that we note is the systems perspective. A number of theories describe innovation as a system of interacting parts. These systems variously operate at a national level (Bengt-Ake, 1992; Nelson and Rosenberg, 1993), at a regional level (Cooke et al., 1998), or at the scale of an entire industry (Malerba, 2002). The innovation ecosystem, a branch of innovation systems approaches, focuses more on the relationships between actors and actor groups in regional and sectoral innovation systems (Autio et al., 2014; Mazzucato and Robinson, in press). A related concept – functions of innovation systems – examines the required parts necessary for an innovation system to fully thrive (Hekkert et al., 2007). This literature often examines the performance of R & D and is utilized in business and management literature. While these are at the *meso* and *macro* levels of analysis (sectors, nations, etc.), they provide interesting insights into the types of dynamics that drive and direct TDSs. A summary is provided in Table 1.

This review reveals a concerted effort to collect data, construct theories, and develop new methods to analyze technological development. A common need within these approaches is to identify the key actors and stakeholders and recognize how these elements fit together and operate as a system. Moreover, a systematic way of doing this can integrate different datasets so that analysts can zoom into micro-level aspects of an emerging technology field, or zoom out to whole systems of innovation.

This paper contributes to this need, placing an emphasis on tech mining as an approach to furnish insights into TDSs. This paper also addresses a serious lack of methods that can integrate tech mining data and produce useful graphical representations for discussion and policy advice.

3. Research objectives

Innovation is currently considered increasingly crucial to driving jobs and growth, as well as effectively dealing with the negative ramifications of historical economic drivers that have led to inequality, unsustainable manufacturing systems, and a polluting energy system that is based on unsustainable energy sources (Hekkert and Negro, 2009). Studying innovation is therefore important.

As the literature review above highlights, several of the proposed approaches to innovation systems offer similarities, but their models differ in the concepts used and in the actors they identify and emphasize (Johnson, 2001). Among the various methods to capture the essentials of innovation systems, the TDS has demonstrated value by capturing the key institutional actors and contextual factors, spotlighting leverage points to affect outcomes, and identifying technological advantages and commercialization prospects. In a sense, the TDS is a way of positioning data that is potentially useful for many of the different conceptual frameworks described above.

A number of researchers have introduced modifications to improve the representations produced by Wenk and Kuehn's TDS model (Wenk and Kuehn, 1977). Walker (Walker, 2000) described a systematic process for examining complex public policy choices to assist policymakers in choosing preferred courses of action. Guo et al. (Guo et al., 2012a) introduced a new cross-charting method that appears effective at associating novel technology-enabled capabilities to gain functional advantages and link those functions to potential applications. Porter et al. (Porter et al., 2015) identified contextual forces and factors involving multiple TDS elements to address sub-systems and attendant technical and market infrastructures. These explorations frame the technology within its broader environment and facilitate consideration of the contextual factors together to help manage innovation processes.

The TDS has also recently been presented as a core part of the “Forecasting Innovation Pathways” (FIP) approach (Guo et al., 2012b; Robinson et al., 2013). FIP combines a range of Future-Oriented Technology Analysis (FTA) tools to assist decision makers in discovering opportunities (and threats) to achieve successful innovation while recognizing the inherent uncertainties of innovation pathways.

In this paper, we exploit Science, Technology and Innovation (ST & I) data resources to generate a landscape of the R & D activities, commercial performance factors, and pertinent policy environments. Ultimately, we hope our TDS model can offer insights into technological development, including:

- profiling internal and external surroundings regarding uncertainty,

Table 1
Three perspectives on the TDS.

Perspectives	Technology perspectives	Delivery perspectives	Systems perspectives
Related concepts	Technology roadmapping	Advocacy coalition theory Growth coalition theory Opportunity structures Triple helix Actor-network theory Socio-technical networks Techno-economic networks Stakeholder analysis Transitions management	Functions of innovation systems National systems of innovation Regional systems of innovation Sectoral systems of innovation Socio-technical networks Techno-economic networks Innovation ecosystems

Table 2
The framework and candidate tools to build a TDS.

Stage	Data resources	Analyses	Candidate tools
1) Identify macroeconomics and policy environment	● Policy documents ● Funding archives ● Market reports	● Policy environment analyses ● Funding environment analyses ● Market environment analyses	● Trend analyses ● Literature review
2) Specify the key public and private institutions	● Scientific publications ● Applied patents	● Core research institutions ● Leading patent assignees	● Bibliometric analyses ● Research profiling
3) Address the core technical complements and their owners	● Patent records ● Patent legal documents	● Top actors and topic analyses ● Technology transfer analyses	● Term clumping ● Social network analyses
4) Depict the market prospects and evaluate the potential impacts	● Commercial data ● Interview transcriptions	● Potential impact assessment ● Specific opportunities analyses	● Tech mining ● Technology opportunities analysis

risk, benefits, and consequences;

- distinguishing the main participants engaged in the delivery process and their roles in the associated value chains;
- linking the essential institutions that generate innovations with prospective market applications that benefit industry sectors and individual customers; and
- assembling a technical engine for implementing the critical problem-structuring phase of a forecast.

4. Framework and methodology

Our systematic approach for building a TDS model is constructed in four stages.

The **first stage** is to identify the relevant macroeconomic and policy environment, including market competition, financial investment, and industrial policy. This provides the overall landscape of the technology under study – in this case, Big Data – and is where value chains will emerge (if they emerge). It is the world of investment and policy, and, thus, is populated by those interested in the intelligence the TDS will provide. These are likely to be decision makers and investors wishing to identify promising directions to target their resources to maximize returns on investment (Robinson and Propp, 2008). This stage attempts to track the evolution of the landscape by: identifying related policy documents; probing how national funding agencies offer financial support to accelerate scientific discovery; and elucidating the activities and interests of business communities regarding the market environment.

The **second stage** involves specifying the key public and private institutions that play an important role in the delivery of applications stemming from the focal technology – i.e., identifying the actors along the supply chain. Scientific publication and patent data are used to identify the actors that affect the success of the innovation process. On the one hand, emphasis is placed on the influential institutions showing capacity in knowledge and technological development, but also on those showing signs of collaboration and competition. On the other hand, the evolution of a technological development may indicate that cooperative R & D is becoming important. With this in mind, a close eye is kept on companies that are facilitating the target technology, developing the innovation, and taking it to market. Research profiling (Porter et al., 2002), a method that seeks knowledge from a body of literature beyond that obtainable by digesting individual pieces, is applied to derive information about the research communities and patent assignees.

The **third stage** focuses on addressing the core technical components and their owners, then traces the interactions through information linkages and technology transfers. In a complex technology system, it is important to figure out the topical terms that can indicate the significant topics during the emergence of a technology. Therefore, it is necessary to dig deep at a textual level rather than parse basic bibliometric indicators. To do this, focus is given to the abstract and title records in the search results of the R & D publication and patent documents that pertain to the technology of interest, as these serve as the sources for profiling the technological innovation. An inductive method, called term clumping (Zhang et al., 2014), is then applied to clean and consolidate the topical content in these text sources to constitute meaningful technological topics and their interactions (Zhang et al., 2016). Furthermore, a close eye is kept on tracing the topical technologies and technology transfers among the different stakeholders who can affect, or are affected by, the information ecosystem in a positive or negative manner.

The **fourth stage** depicts the envisioned market prospects. ST & I data sources offer abundant intelligence for landscaping R & D. Other databases compile information on commercial, policy, and popular responses to gain more comprehensive insights to help forecast innovation pathways. According to the theory of technology adoption, innovation diffusion is the process by which an innovation is communicated through certain channels over time among the members of a social system (Rogers, 2010). This stage combines three approaches – tech mining (Porter and Cunningham, 2004), multi-path mapping (Robinson and Propp, 2008), and expert review – to address the full developmental pathways (i.e., to consider the implications of the processes as well as the resulting applications).

The overall framework for constructing a TDS model that characterizes the supply side of technology emergence is summarized in Table 2.

5. Data

As shown in Table 2, this paper explores empirical insights drawn from different types of documents (e.g., policy reports, funding proposals, scientific articles, and patent assignment information) to contribute to an enriched TDS model for the study of the supply side of BDA – with a focus on the United States (US). The US is a good locale because their innovation system is well placed to take advantage of the advances in BDA. Over the past decade, the US has been prominent in the digital economy, particularly in social networking enterprises. Moreover, the US government has positioned BDA as a socio-economic revolution and is seeking ways to ensure the country stays globally competitive in this area (Executive Office of the President, 2014).

According to a recently published approach to creating search strategies for 'Big Data' (Huang et al., 2015), considering multiple data sources, this paper strikes a balance between accuracy and recall. The final search strategy we applied was:

TS = ((“Big Data” or Bigdata) OR (((Big Near/1 Data or Huge Near/1 Data) or “Massive Data” or “Data Lake” or “Massive Information” or “Huge Information” or “Big Information” or “Large-scale Data” or Petabyte or Exabyte or Zettabyte or “Semi-Structured Data” or “Semi structured Data” or “Unstructured Data”) AND (“analytic” OR “analyz*” OR “analys*”))).*

Creating a useful TDS model for BDA is a complex task. The information needed is spread across various sites and databases; therefore, it is important to obtain technical information from multiple data sources. Compared to traditional ST & I data, funding proposals are granted by national governments with the aim of supporting academic institutions and R & D departments to conduct basic research that

Table 3
Data sources and descriptions.

Data	Data source	Records
Policy documents	White House (https://www.whitehouse.gov)	~10
Scientific publications	Web of Science (http://apps.webofknowledge.com)	1599
Patent applications	Thomson Innovation (https://www.thomsoninnovation.com)	765
Funding archives	National Science Foundation (https://www.nsf.gov)	830
Commercial records	ProQuest (http://search.proquest.com)	9977

focuses on new ideas, concepts, and potential innovative actions (Huang et al., 2016). Policy documents are essential for tracing the administrative means governments have used to promote the development of certain technology or industry elements. Commercial data are an important source of gauging the direction of the market. The data sources we used with brief descriptions are presented in Table 3.

We further explored the annual activity trends of the data sources and illustrate the results in Fig. 1 (the trend for policy documents has not been shown due to the limited record set). All data sources have increased in terms of the number of records in the past few years, especially since 2013. The trends for scientific publications and funding archives have followed a similar path. Patent applications saw a rapid increase in 2014 but declined in 2015 – a data artifact reflecting the substantial time lag between submitting an application and opening that record to the public. The trend for commercial records reveals that industry has paid a great deal of attention to Big Data since its emergence as a hot topic; however, the growth rate has slowed since 2013.

6. Case study: the TDS for Big Data & Analytics in the US

A case study of BDA in the US illustrates how the TDS methodology can be used to identify the elements that are most likely to be affected by the speed, customization, and volume of an innovation. Below we provide, in advance, the composite TDS that is the output of the analyses that follow, shown as Fig. 2.

6.1. Relevant macroeconomic and policy environment

As per the first stage of the TDS, the macro-environment of BDA in the US was profiled by reviewing the policies and reports issued by the US government, shown in Table 4 below and visible in the bottom-center of Fig. 2. It is clear that the Obama Administration attached importance to BDA. Several policies were issued to promote government transparency around Big Data, each aiming to improve public trust and promote the efficiency and effectiveness of government. The Administration also realized the great value and opportunities brought by such a fast-growing volume of digital data. Its most influential initiative in this effort, the “Big Data Research and Development Initiative”, facilitated six Federal departments and agencies to invest more than $200 million combined to improve the tools and techniques needed to access, organize, and glean discoveries from huge volumes of digital data. Despite the challenges arising from privacy issues, the US government's intention to seize the opportunities and potential socio-economic benefits promised by BDA is clear. From a political perspective, the US government is promoting the development of BDA.

Among the six federal departments most concerned with BDA, the National Science Foundation (NSF) is perhaps foremost in the quest to derive knowledge from data, establish the infrastructure to manage, curate, and serve data to communities, and foster new approaches to education and workforce development. The NSF website lists more than 20 active or archived programs that provide awards to develop Big Data algorithms, promote Big Data analytics techniques, advance Big Data applications, and so on. The top 10 BDA-related grant programs offered by NSF during 2008–2015 are listed in Table 5. The “Information Integration & Informatics” program accounts for the largest number of projects, and the “Big Data Science & Engineering” program accounts for the most capital support. Scientific funding plays an essential role in individual scientific research, university discipline engagement, and national innovation system patterns (Lok, 2010), and US researchers have a wide range of funding and resource acquisition options to conduct studies related to BDA.

Based on the “2016–2026 Worldwide Big Data Market Forecast” published by Wikibon, a community founded to deliver the most actionable and real-time information available in the marketplace, we conclude that the main areas in the Big Data field will keep growing over the next few years, as shown in Fig. 3. Big Data software is the most promising area, with its market value expected to reach $42.7 billion. Big Data apps, analytics, and tools is another area with high potential that could grow from $2.0 billion in 2014 to $23.2 billion in 2026 – an annual growth rate of nearly 23%. Based on market expectations and current development trends, BDA stands to provide huge market opportunities. This can be used in the TDS as an indication of the envisioned products and services that are driving development (see the right side of Fig. 2).

6.2. Main participants in the technology delivery process

In the standard model of technological innovation, academic research institutions provide basic research knowledge, akin to a knowledge reservoir, that can be tapped by industry. We identified the top institutions in BDA research and constructed a co-author network using the visualization and exploration software Gephi (www.gephi.org), as shown in Fig. 4. Researchers at Harvard University have published the most manuscripts related to BDA (66 records) and have built the widest co-author network with other universities. University of California, Los Angeles follows (52 records) and shows strong co-operation with both the University of Southern California (36 records)

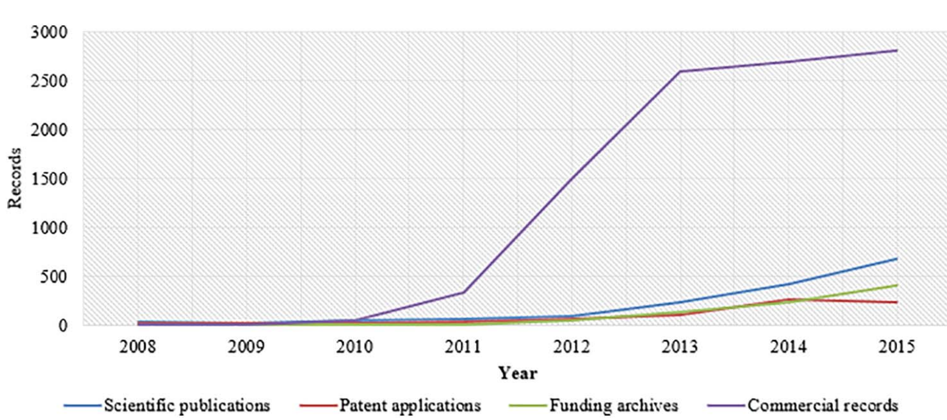

Fig. 1. The trends for the four data sources for 2008–2015.

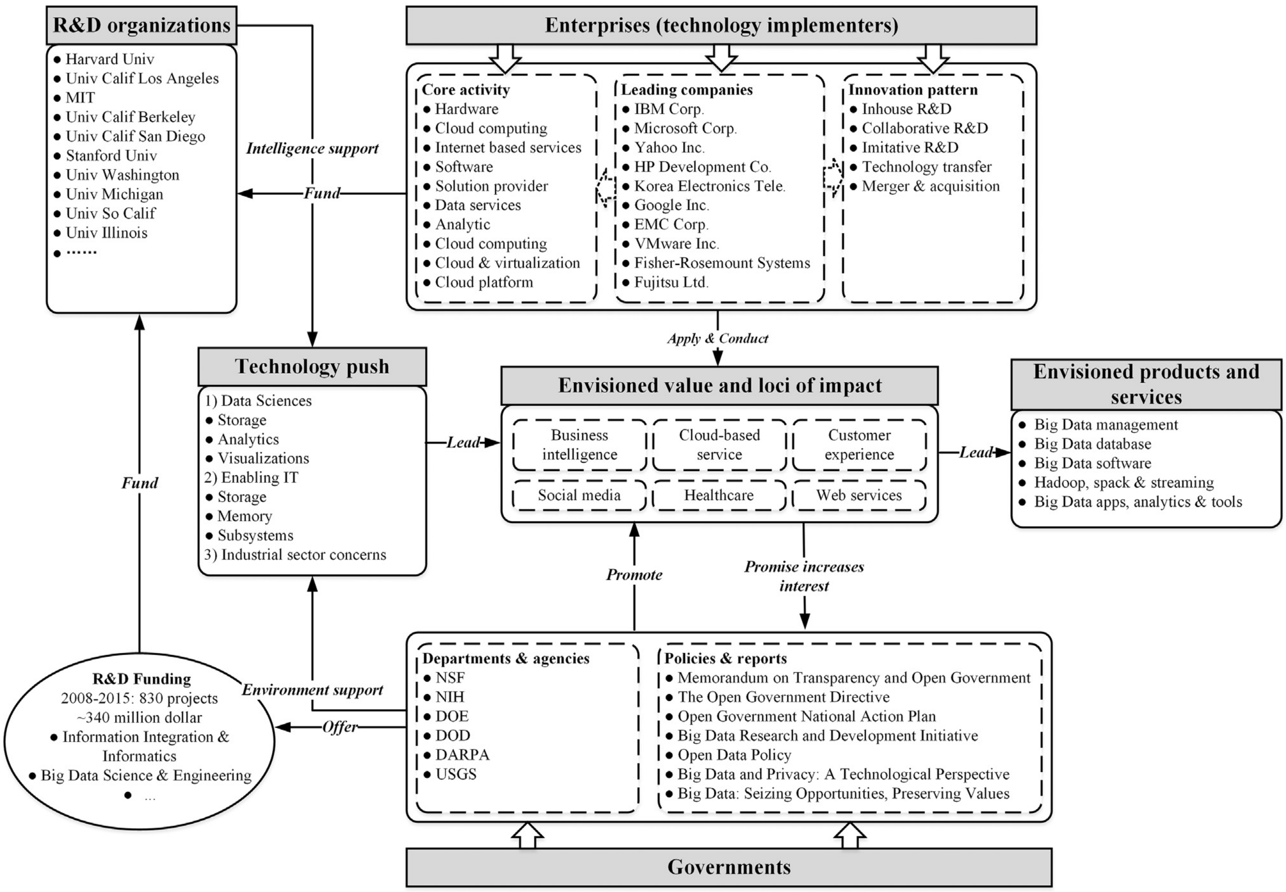

Fig. 2. The TDS for BDA.

and the University of California, San Diego (46 records). MIT stands out in computer science, ranking third in record numbers. Overall, the main US academic institutions in BDA are distributed across various states; most have strong R & D capacity in both basic and applied research. This allowed us to populate the components of the TDS dedicated to key American R & D actors (while recognizing additional R & D within industry and government).

Patents provide an indication of firms, or other actors, who have an active interest in commercialization in a technology field. Corresponding to the main academic institutions, the leading patent assignees in BDA are presented in Table 6. As the Big Data technology and services market is a fast-growing, multi-billion dollar worldwide market, it is unsurprising to see many transnational corporations value BDA. Some provide hardware for data management and warehousing, or Hadoop systems and stream computing, such as IBM, Microsoft, and Fujitsu. Others focus on software or platforms for Big Data solutions to assist decision making in the ideas economy, such as Hewlett-Packard and Fisher-Rosemount Systems. Others still offer internet or cloud-based services that capitalize on their roots as internet search engines, such as Google and Yahoo.

Table 4
Big Data policies and reports issued by the US government.

Year	Policy documents	Main content
Jan 2009	Memorandum on Transparency and Open Government	To create an unprecedented level of openness in government to ensure public trust and establish a system of transparency, public participation, and collaboration.
Dec 2009	The Open Government Directive	To promote accountability by providing (transparently) the public with information about what government is doing.
Sep 2011	Open Government National Action Plan 1.0	To increase public integrity, enhance public access to information, improve the management of public resources, and give the public a more active voice.
Mar 2012	Big Data Research and Development Initiative	To make the most of the fast-growing volume of digital data and improve the ability to extract knowledge and insights from large and complex collections of digital data. This initiative promises to help solve some the nation's most pressing challenges.
May 2013	Open Data Policy	To manage government information as an asset to increase operational efficiency, reduce costs, improve services, support mission needs, safeguard personal information, and increase public access to valuable government information.
Dec 2013	Open Government National Action Plan 2.0	To build a more open, transparent, and participatory US government.
May 2014	Big Data and Privacy: A Technological Perspective	To address challenges to privacy arising from data analytics.
May 2014	Big Data: Seizing Opportunities, Preserving Values	To review how the public and private sectors can maximize the benefits of Big Data while minimizing its risks. It also identifies opportunities for Big Data to grow the economy, improve health and education, and make the nation safer and more energy efficient.
Oct 2015	Open Government National Action Plan 3.0	To promote transparency and accountability in government and build a more open government.

Table 5
Top 10 programs supported by the NSF, 2008–2015.

No.	Program(s)	Funded records	Funding ($)
1	Information Integration & Informatics	49	12,958,431
2	Big Data Science & Engineering	44	29,329,333
3	Statistics	39	6,266,046
4	Campus Cyberinfrastructure (CC-NIE)	30	13,868,352
5	Computer Systems	27	8,840,234
6	Communication & Information Foundations	25	6,801,422
7	Industry/University Cooperation Research Centers	22	1,718,283
8	Algorithmic Foundations	17	4,598,514
9	Software & Hardware Foundation	17	5,507,270
10	Information Technology Research	14	6,873,425

6.3. Technical components linkages and technology interactions

Different patent assignees can share common interests while placing emphasis on different foci. Information on technological foci can be extracted from Cooperative Patent Classification (CPC) data, a new classification that covers all EPO and US classified documents. A co-occurrence network of the top 10 patent assignees and their technical foci is presented in Fig. 5. It is clear that IBM has a strong technological presence in information retrieval, database structures, parallel computing, and algorithms. Google focuses on a range of technologies, including algorithms, program code, data protection, etc. Other assignees have their own core advantages. Microsoft is strong in homomorphic encryption and social networking analysis. VMware is good at data storage and resource distribution. Hewlett Packard has advantages in marketing commerce and monitoring and detection. EMC has superiority in specific field applications and cloud platforms. Yahoo performs well in information retrieval and software deployment. Fisher-Rosemount Systems leads the field in network communications and electric control.

Enterprises are gradually beginning to obtain external technological resources, rather than simply relying on internal R & D. As they face rapid growth of technology, foreshortened refreshment cycles, and diversified consumer demand, the assignment of patent rights is an effective way to obtain competitive technological advantages. Such activities can be tracked by tracing the reassignment information in legal status. A snapshot of the legal status of BDA patents in the US is shown in Fig. 6. We were surprised to find that, from a total of 765 patents, 561 have been assigned from the stakeholders to the actual patent assignees. Furthermore, some patents have been transferred more than once. In the BDA field, technology transfer activities appear to be very active. Technology transactions and technology mergers and acquisitions are important ways to gain a technical advantage. To better trace the stakeholders in the process of technology transfer, we read the assignment information of these 561 records. The results reveal that most patents are assigned from individuals (most of them are the staff of patent assignees) who convey their inventions to specific assignees when they make the patent application. This strategy can have mutual benefits for companies and staff; companies can enhance their innovation capacity while R & D staff receive an appropriate technology transfer fee. For example, 85 of the 102 BDA patents owned by IBM were transferred from their employees. Similar situations are found in other leading companies. Alternatively, some transfers may be from a parent company to a subsidiary or branch, as in the case of Microsoft in passing ownership of five patents to Microsoft Technology Licensing to give it the legal power to litigate those patents.

6.4. Envisioned market prospects and potential impacts

BDA offers businesses a window into diverse streams of information. To obtain a sense of the Big Data field, key term analysis offers an effective way to investigate topical emphases. Here, term clumping was applied to the commercial records from ProQuest using the VantagePoint text-mining tool to discover knowledge from the search results of patent and literature databases. We also invited several domain researchers to check the initial terms list. To ensure the analysis focused on potential commercial applications, common domain terms were deleted (Big Data, data analysis, etc.). Ultimately, 60 key terms close to our research targets were derived. Network analysis was conducted using Gephi, and the top 60 terms were categorized into six clusters through modularity analysis (Blondel et al., 2008). Each cluster indicates a priority topic in the field, as shown in Fig. 7. The different colors represent different clusters and the size of the node indicates the term frequency as follows: (1) business intelligence, predictive analytics, decision making, etc. (purple); (2) social media, social gaming, public relationships, etc. (pink); (3) healthcare, life sciences, pharmaceuticals, etc. (blue); (4) cloud-based services, business values, smartphones, etc. (brown); and (5) web services, Amazon web services, opera solutions, etc. (yellow); (6) customer experience, cybersecurity, supply chains, etc. (green).

We identified and validated 18 candidate BDA impacts through the literature review, team discussions, and feedback from colleagues – see Table 7. This is key to understanding the perceived value of BDA and which functionalities provide value for exploitation and translation into

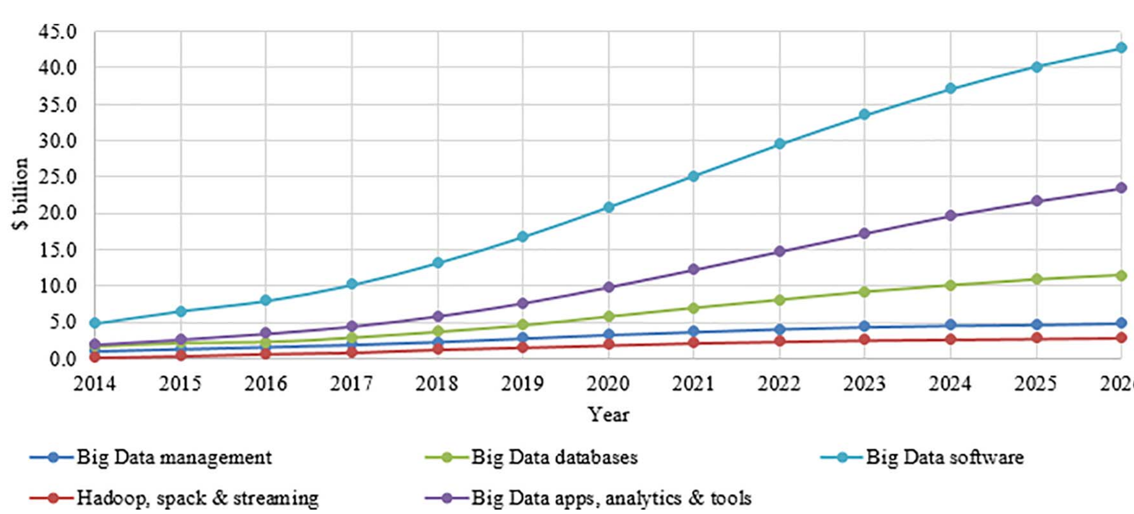

Fig. 3. 2016–2026 worldwide Big Data market forecast.
Data source: Wikibon Big Data project, 2016.

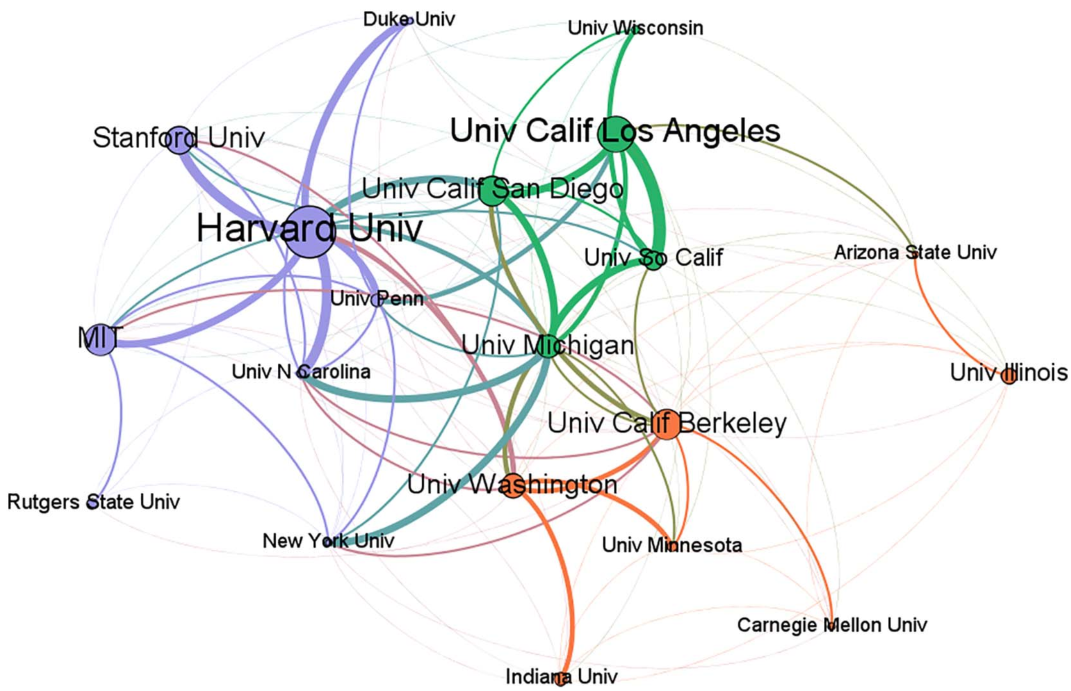

Fig. 4. Co-author network of the main academic institutions in BDA.

Table 6
Leading patent assignees in BDA.

No.	Patent assignees	Records	Country	Classification of core activity
1	IBM Corp.	102	USA	Hardware + cloud computing
2	Microsoft Corp.	28	USA	Hardware + cloud computing
3	Yahoo Inc.	25	USA	Internet-based services
4	HP Development Co.	19	USA	Software + solution provider
5	Korea Electronics Telecommunications	15	South Korea	Hardware + communication
6	Google Inc.	14	USA	Internet-based services and data analytics
7	EMC Corp.	10	USA	Cloud computing using Hadoop
8	VMware Inc.	10	USA	Cloud & virtualization software and service
9	Fisher Rosemount Systems Inc.	9	USA	Industry-specific solution provider
10	Fujitsu Ltd.	9	Japan	Hardware + cloud computing

products or services (see the central box in Fig. 2).

To further explore the potential impacts on the dimensions of likelihood and importance, opinions from domain experts were solicited through an online survey. Details about the survey process and results analysis can be found in our paper related to the BDA technology assessment (Liu et al., 2016). The final estimated impact values are shown in Fig. 8. The results indicate that almost all of the 18 potential impacts are highly likely to occur, and addressing most would require the US government to consider policy actions. Given that the 18 impacts chosen for the survey were mainly compiled from existing literature and published reports, these 'highly likely' estimations are unsurprising. However, the survey respondents suggested some additional impacts that ought to be considered, such as data quality, risk management of emerging technology development, and professional education about BDA.

7. Discussion

In this paper, we propose a TDS model to characterize the supply side of technology emergence. It proves to be useful in identifying the different elements of an emerging technology supply chain, as well as some of the macroeconomic and policy factors that impinge on its development. We also identify the potential application areas to which the supply chain will provide added value and socio-economic benefit. We draw on multiple data sources related to political, economic, academic, technical, and commercial market factors, and apply multi-dimensional analyses, including a literature review, bibliometric analyses, and social network analyses. Each element of the TDS is based on a different type of data that collectively builds a rich picture that is essential to diagnose the status of the supply side of, in this case, the BDA industry.

This systematic approach to constructing an enhanced TDS is divided into four main stages: (1) profiling the internal and external surroundings of the target technology in terms of uncertainty, risk, benefits, and consequences; (2) distinguishing the main participants engaged in the delivery process and their roles in the corresponding value chains; (3) linking the essential institutions that generate innovations with prospective market applications that benefit industry sectors and individual customers; and (4) assembling a technical engine for implementing the critical problem-structuring phase of a forecast.

BDA is a hot topic across many sectors and, hence, was used as the subject of our case study. It is clear that the US government (as of the Obama administration) attaches great importance to the development of BDA and supports academic institutions and industrial communities through national research funding and promotion policies. IBM, Microsoft, and some other leading enterprises stand out in the development of technological capacity. They are strong in different

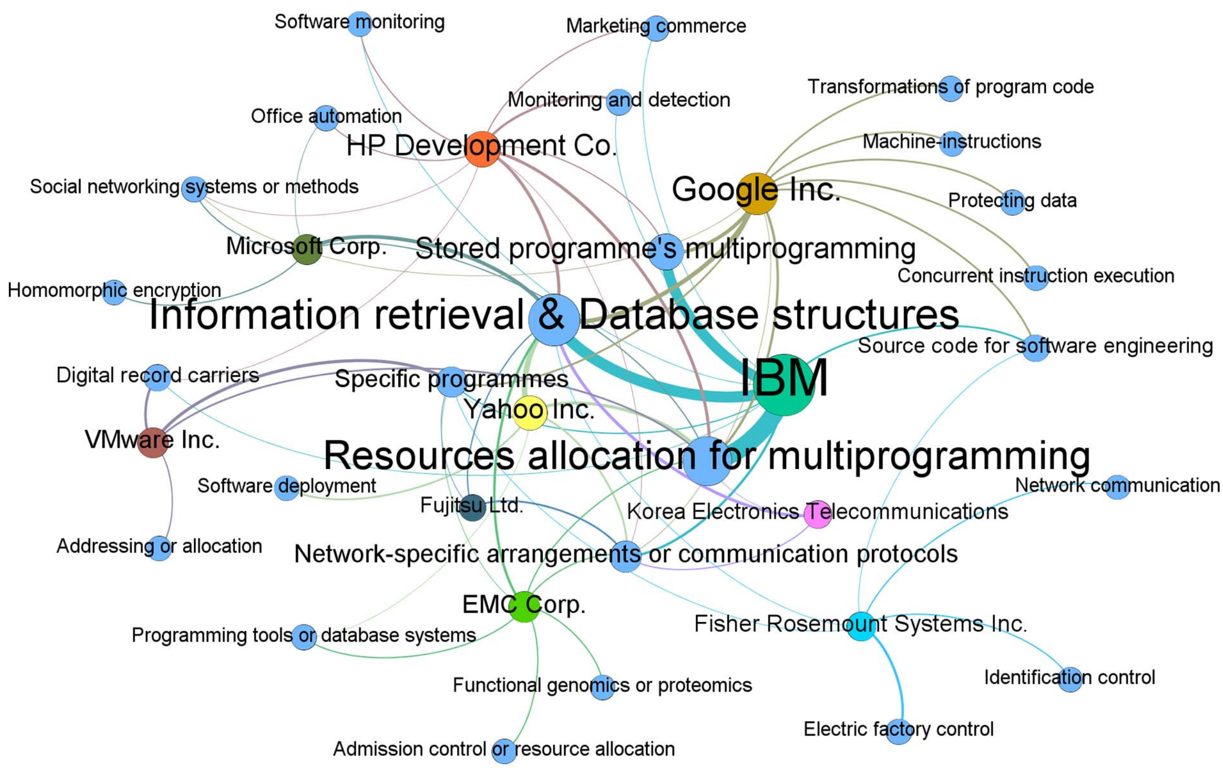

Fig. 5. Co-occurrence of leading patent assignees and technical foci.

technological foci of various background and development components. Interestingly, most of their intellectual property has been acquired from other entities, especially individual inventors. Business intelligence, cloud-based services, customer services, social media, healthcare, and web services are among six of the foci extracted from a large amount of commercial information. Almost all of the 18 potential impacts of BDA are deemed important and are likely to occur in the near future. However, the challenges and risks brought by BDA seem compounded by limitations in traditional technologies; these seem to warrant particular attention, both from the technological and policy side.

This paper also provides insight into some of the means by which Big Data companies are gaining value from their data, and suggest that two of the big impacts of Big Data concern its openness and control. Furthermore, we discuss how our methodology might provide additional insights into the speed and rapidity of Big Data advancements.

Our analytical approach takes advantage of the rich repositories of electronic information to profile R & D, and to understand the business activities that pertain to the NEST in question – i.e., our approach 'tech mining' via database searches and analyzes the retrieved records. However, TDS modeling is a FTA tool. The complexity of innovation processes in new and emerging technology fields means that it is hard to build an innovation system model based solely on analyzing organized databases. Therefore, such quantitative intelligence should be supplemented with expert opinions, garnered via interviews and workshop-style approaches.

8. Conclusions

This paper contributes to technology management and opportunity identification for complex innovations (see Fig. 9). The presented approach focuses on improving techno-centric assessment and foresight to describe emerging and evolving supply chains and to make clear the relevant dynamics to inform decision making and intervention. The approach helps pull together many different types of data into a coherent map of elements that will shape the eventual supply chain of an emerging technology as it spawns innovative products and services. The intent is that the findings can be readily interpreted by those involved in the technology development process, thus, providing a useful tool for

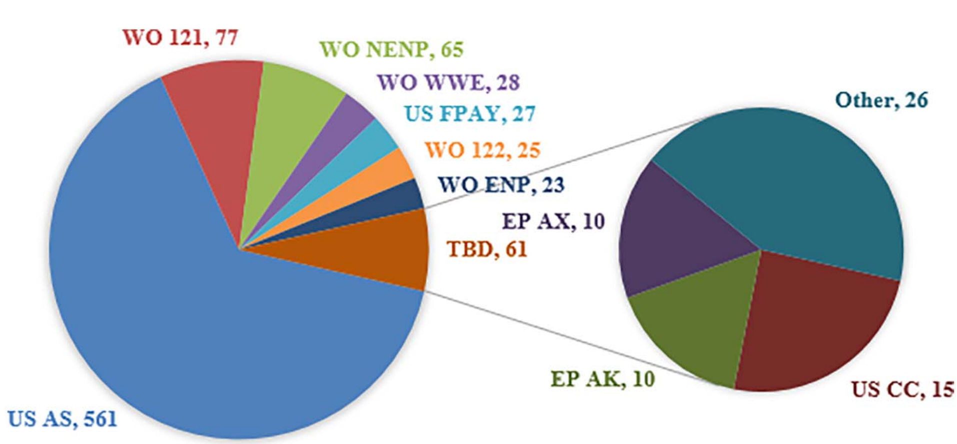

Fig. 6. The legal status of BDA patents in the US.
Note: The last number in each item concerns the records of responding legal status, e.g. "US AS, 561" represents 561 patents were ever assigned by USPTO.
Note: US AS: Assignment; WO 121: The EPO has been informed by WIPO that EP was designated in this application; WO NENP: non-entry into the national phase; WO WWE: WIPO information: entry into national phase; US FPAY: expired due to failure to pay maintenance fee; WO 122: PCT application non-entry into the European phase; WO ENP: entry into the national phase; US CC: certificate of correction; EP AK: designated contracting states; EP AX: extension of the European patent.

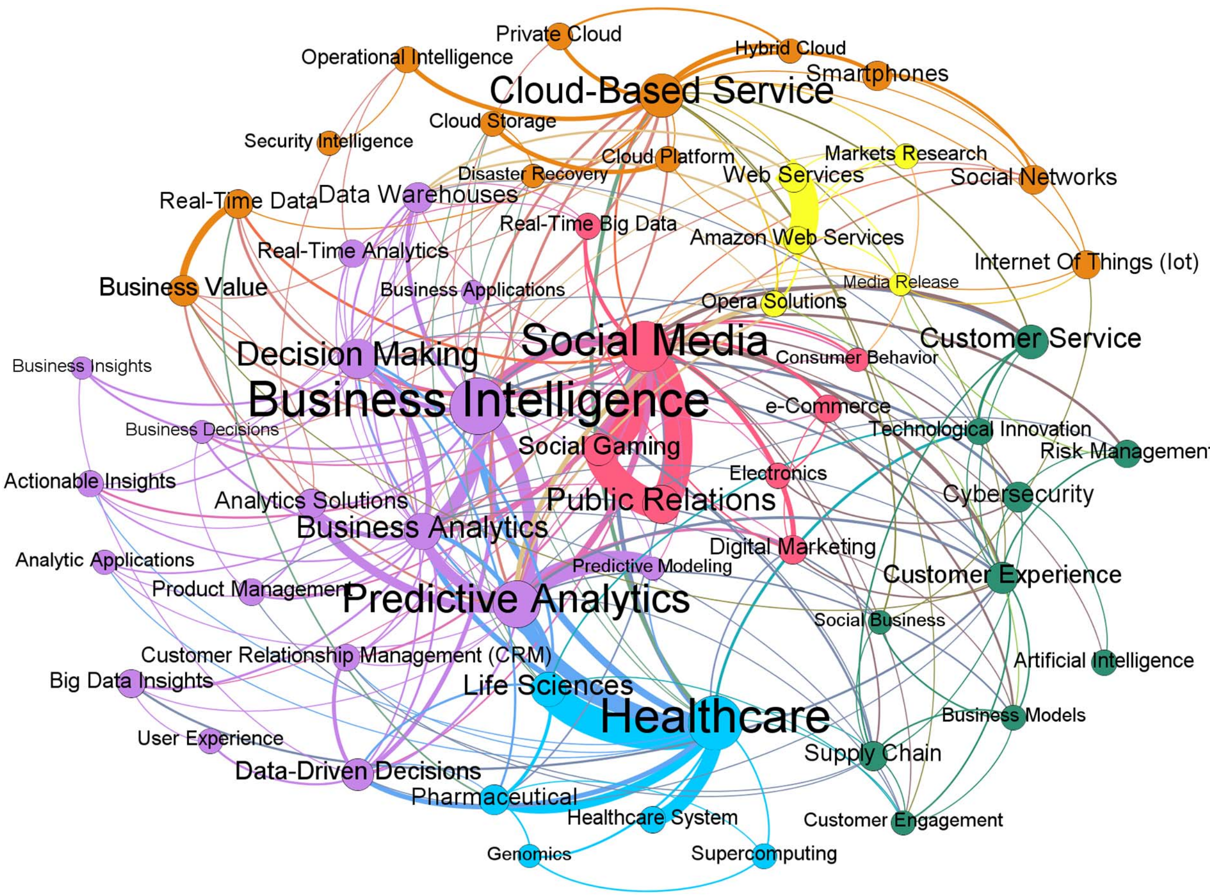

Fig. 7. Cluster analysis and co-occurrence networks of the top 60 key terms.

Table 7
Definitions of 18 potential BDA impacts.

Node	Node definition
A	Massive data collections combined with increasingly powerful computing and Big Data algorithms improve prediction significantly (e.g., weather, crime).
B	Databased understanding of “grand challenges” leads to substantial improvements (e.g., energy).
C	Multiple BDA applications greatly reduce terrorism.
D	As resources are deployed more effectively, new sectors open, providing new jobs on a large scale.
E	Widespread use of BDA leads to substantial wealth redistribution.
F	Overconfidence in data-based analyses leads to critical errors.
G	Data compiled for one purpose are misinterpreted in analyses for other purposes to a significant degree.
H	Substantial automation via BDA processes reduces jobs for analysts and managers.
I	Popular/political backlash against BDA leads to major extremist actions.
J	Extensive data sharing by organizations greatly expands inter-organization cooperation (networking).
K	Organizations use more extensive and accurate modeling and prediction to meet market desires better (and major profits).
L	Organizations must deal with increased security threats due to BDA.
M	Organizations compete rather intensely to control data access and use.
N	Individual consumers use more data and better analyses to enrich their market options.
O	Effective monitoring detects threats earlier, thereby protecting individuals effectively.
P	Richer data availability leads to better individual decisions on a wide scale (e.g., smarter shopping, education, and health choices).
Q	Privacy abuses escalate substantially.
R	As automated BDA processes take over much decision-making, face-to-face human engagement diminishes.

Note: A–I indicate the impacts at a national level, J–M show the impacts at industry level, and N–R show impacts at an individual level.

reflexive innovation management.

The TDS focuses on the actors and activities on the supply side of innovation – in other words, those who are involved in the promotion of new technologies. Promotion, here, means those who are involved in producing and pushing to develop a new technology to emerge as potential options for markets and for society. Of course, the story of technology emergence is about both emergence and uptake – where uptake is dependent on both markets and civil society. Technology emergence is also about promotion and control. The TDS, for example, identifies the public agencies that fund a new and emerging technology, but this does not include the public agencies that regulate new products and other activities. That is part of a broader picture, where other conceptual frameworks can be mobilized to characterize emergence and inform technology assessment studies – for example, identifying actual and potential socio-economic impacts (see Table 1). Thus, although being useful in its own right, we envision the TDS being connected with other frameworks to contribute to a robust analysis of the broader socio-technical system that contributes to socio-economic

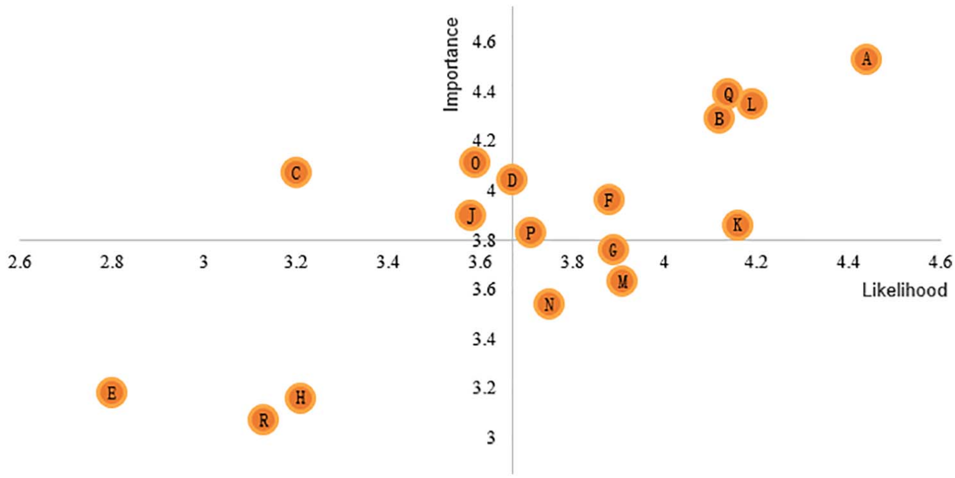

Fig. 8. Estimated impacts of BDA based on a survey.

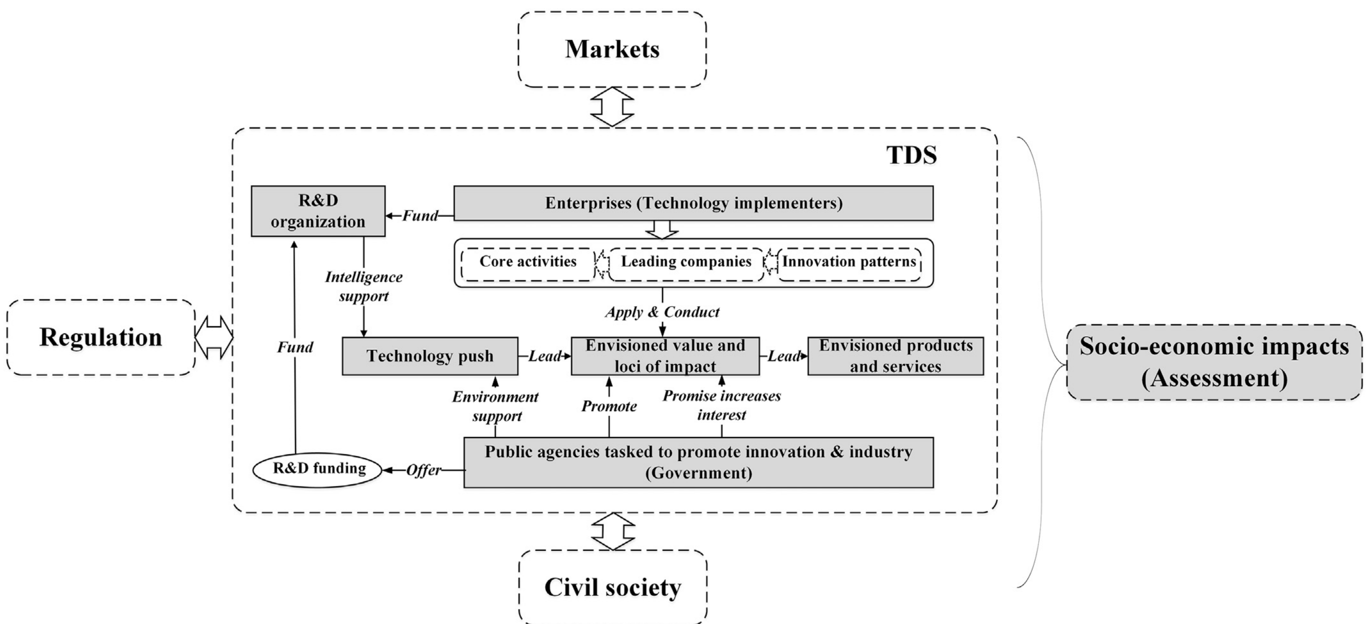

Fig. 9. The TDS as part of a large perspective of innovation (eco)systems.

impact (Fig. 9).

Building a TDS model can generate valued insights in several ways. First, in forcing the analyst to consider contextual forces, it drives us beyond a too-narrow technological focus. That widens the scope of inquiry, even for a supply-side orientation. Second, a TDS can help assess factors vital to successful innovation. A classic case used a TDS model for solar energy development to make it abundantly clear why the residential adoption of new solar technology had not been a success (Ezra, 1975). Namely, the path from R & D in government labs to enterprises that could commercialize the technology was a non-starter; at the time, there were no incentives for that. Furthermore, would-be equipment manufacturers would confront an incredibly distributed market of home builders (mainly individuals), who would confront multiple building codes. To cap the situation, financing for such augmentations to houses faced an uphill struggle from ill-formed buyer demand, further impeded by conservative lending organizations. For BDA, one could similarly track forward using the TDS to identify what would be entailed to accomplish given innovation targets.

A further addition to the TDS would be a similar user-centric model. In such an approach, the focus shifts from a promising technological option, to a situation of user-centered choices, which would necessarily be broader than BDA. What are the current alternatives for BDA? What does BDA offer in terms of added value, and how do users assess and compare BDA vis-à-vis the incumbent situation (or alternatives)? Such a user-centric approach would be a useful next step but would require a specific focus – BDA in healthcare systems, for example – to be able to model the system, identify the alternatives, and identify the key stakeholders involved in "selecting-in" and "selecting-out" new options. This is further work for our team to address.

Acknowledgements

We acknowledge support from the US National Science Foundation (Award No. 1527370), the Junior Fellowships of CAST Advanced S & T Think-tank Program (Grant No. DXB-ZKQN-2017-020), the General Program of the National Natural Science Foundation of China (Grant No. 71673024) and the European Union Seventh Framework Programme for ICT (Grant No. 285593). The findings and observations contained in this paper are those of the authors and do not necessarily reflect the views of the supporters or the sponsors.

References

Autio, E., Kenney, M., Mustar, P., Siegel, D., Wright, M., 2014. Entrepreneurial

innovation: the importance of context. Res. Policy 43, 1097–1108.
Bengt-Ake, L., 1992. National Systems of Innovation: Toward a Theory of Innovation and Interactive Learning. Pinter Publisher, London.
Blondel, V.D., Guillaume, J.L., Lambiotte, R., Lefebvre, E., 2008. Fast unfolding of community hierarchies in large networks. J. Stat. Mech: Theory Exp. 2008, 1–6.
Branscomb, L.M., 1973. Federal support of commercially relevant R & D. Am. Sci. 61, 144–151.
Bryson, J.M., 2004. What to do when stakeholders matter. Public Manag. Rev. 6, 21–53.
Bryson, J.M., Crosby, B.C., Bryson, J.K., 2009. Understanding strategic planning and the formulation and implementation of strategic plans as a way of knowing: the contributions of actor-network theory. Int. Public Manag. J. 12, 172–207.
Callon, M., 1990. Techno-economic networks and irreversibility. Sociol. Rev. 38, 132–161.
Callon, M., Laredo, P., Rabeharisoa, V., Gonard, T., Leray, T., 1992. The management and evaluation of technological programs and the dynamics of techno-economic networks: the case of the AFME. Res. Policy 21, 215–236.
Cooke, P., Uranga, M.G., Etxebarria, G., 1998. Regional systems of innovation: an evolutionary perspective. Environ. Plan. A 30, 1563–1584.
Cunningham, S.W., Kwakkel, J., 2011. Innovation forecasting: a case study of the management of engineering and technology literature. Technol. Forecast. Soc. Chang. 78, 346–357.
Etzkowitz, H., Leydesdorff, L., 2000. The dynamics of innovation: from National Systems and "Mode 2" to a triple helix of university–industry–government relations. Res. Policy 29, 109–123.
Executive Office of the President, 2014. In: House, T.W. (Ed.), Big data: seizing opportunities, preserving values, (Washington, D.C.).
Ezra, A.A., 1975. Technology utilization: incentives and solar energy. Science 187, 707–713.
Freeman, E.R., 1984. Strategic Management: A Stakeholder Approach. Cambridge University Press, Cambridge, MA.
Giget, M., 1997. Technology, innovation and strategy: recent developments. Int. J. Technol. Manag. 14, 613–634.
Green, K., Hull, R., McMeekin, A., Walsh, V., 1999. The construction of the techno-economic: networks vs. paradigms. Res. Policy 28, 777–792.
Guo, Y., Xu, C., Huang, L., Porter, A., 2012a. Empirically informing a technology delivery system model for an emerging technology: illustrated for dye-sensitized solar cells. R D Manag. 42, 133–149.
Guo, Y., Ma, T., Porter, A.L., Huang, L., 2012b. Text mining of information resources to inform forecasting innovation pathways. Tech. Anal. Strat. Manag. 24, 843–861.
Hekkert, M.P., Negro, S.O., 2009. Functions of innovation systems as a framework to understand sustainable technological change: empirical evidence for earlier claims. Technol. Forecast. Soc. Chang. 76, 584–594.
Hekkert, M.P., Suurs, R.A.A., Negro, S.O., Kuhlmann, S., Smits, R.E.H.M., 2007. Functions of innovation systems: a new approach for analysing technological change. Technol. Forecast. Soc. Chang. 74, 413–432.
Huang, Y., Schuehle, J., Porter, A.L., Youtie, J., 2015. A systematic method to create search strategies for emerging technologies based on the Web of Science: illustrated for 'Big Data'. Scientometrics 105, 2005–2022.
Huang, Y., Zhang, Y., Youtie, J., Porter, A.L., Wang, X., 2016. How does national scientific funding support emerging interdisciplinary research: a comparison study of Big Data research in the US and China. PLoS One 11, e0154509.
Johnson, A., 2001. In: Functions in innovation system approaches. Nelson and Winter Conference, Aalborg, Denmark. pp. 12–15.
Kappel, T.A., 2001. Perspectives on roadmaps: how organizations talk about the future. J. Prod. Innov. Manag. 18, 39–50.
Kemp, R., Schot, J., Hoogma, R., 1998. Regime shifts to sustainability through processes of niche formation: the approach of strategic niche management. Tech. Anal. Strat. Manag. 10, 175–198.
Kitschelt, H.P., 1986. Political opportunity structures and political protest: anti-nuclear movements in four democracies. Br. J. Polit. Sci. 16, 57–85.
Latour, B., 2005. Reassembling the Social: An Introduction to Actor-network-theory. Oxford university press, New York.
Liu, J., Guo, Y., Porter, A.L., Huang, Y., 2016. A systematic method for technology assessment: illustrated for 'Big Data'. In: 2016 Portland International Center for Management of Engineering and Technology (PICMET 2016), Honolulu, Hawaii, USA, pp. 2762–2769.
Lok, C., 2010. Science funding: science for the masses. Nature 465, 416–418.
Malerba, F., 2002. Sectoral systems of innovation and production. Res. Policy 31, 247–264.
Mazzucato, M., Robinson, D.K.R., 2017. Co-creating and directing innovation ecosystems? NASAs changing approach to public-private partnerships in low-earth orbit. Technol. Forecast. Soc. Chang. http://dx.doi.org/10.1016/j.techfore.2017.03.034. (in press).
Mitroff, I., 1983. Stakeholders of the Organizational Mind. Jossey-Bass, San Francisco, CA.
Nelson, R.R., Rosenberg, N., 1993. Technical innovation and national systems. In: Nelson, R.R. (Ed.), National Innovation Systems: A Comparative Analysis. Oxford University Press, Oxford, pp. 3–22.
Phaal, R., Farrukh, C.J.P., Probert, D.R., 2004. Technology roadmapping—a planning framework for evolution and revolution. Technol. Forecast. Soc. Chang. 71, 5–26.
Porter, A.L., Cunningham, S.W., 2004. Tech Mining: Exploiting New Technologies for Competitive Advantage. John Wiley & Sons.
Porter, A.L., Rossini, F.A., Eshelman-Bell, J., Jenkins, D.D., Cancelleri, D.J., 1985. Industrial robots — a strategic forecast using the technological delivery system approach. IEEE Trans. Syst. Man Cybern. SMC-15, 521–527.
Porter, A., Kongthon, A., Lu, J.-C., 2002. Research profiling: improving the literature review. Scientometrics 53, 351–370.
Porter, A.L., Cunningham, S.W., Sanz, A., 2015. Advancing the forecasting innovation pathways approach: hybrid and electric vehicles case. Int. J. Technol. Manag. 69, 275–300.
Raven, R., Schot, J., Berkhout, F., 2012. Space and scale in socio-technical transitions. Environ. Innov. Soc. Trans. 4, 63–78.
Rittel, H.W.J., Webber, M.M., 1973. Dilemmas in a general theory of planning. Policy. Sci. 4, 155–169.
Robinson, D.K.R., Propp, T., 2008. Multi-path mapping for alignment strategies in emerging science and technologies. Technol. Forecast. Soc. Chang. 75, 517–538.
Robinson, D.K.R., Huang, L., Guo, Y., Porter, A.L., 2013. Forecasting innovation pathways (FIP) for new and emerging science and technologies. Technol. Forecast. Soc. Chang. 80, 267–285.
Rogers, E.M., 2010. Diffusion of Innovations. Simon and Schuster.
Roper, A.T., Cunningham, S.W., Porter, A.L., Mason, T.W., Rossini, F.A., Banks, J., 2011. Technology forecasting. In: Forecasting and Management of Technology. John Wiley & Sons, Inc., Hoboken, New Jersey, pp. 15–39.
Rosenhead, J., Mingers, J., 2001. Rational Analysis for a Problematic World Revisited: Problem Structuring Methods for Complexity, Uncertainty, and Conflict. John Wiley & Sons, Hoboken, NJ.
Sabatier, P.A., 1988. An advocacy coalition framework of policy change and the role of policy-oriented learning therein. Policy. Sci. 21, 129–168.
Saxenian, A., 1990. Regional networks and the resurgence of Silicon Valley. Calif. Manag. Rev. 33, 89–112.
Walker, W.E., 2000. Policy analysis: a systematic approach to supporting policymaking in the public sector. J. Multi-Criteria Decis. Anal. 9, 11–27.
Walker, W.E., Rahman, S.A., Cave, J., 2001. Adaptive policies, policy analysis, and policy-making. Eur. J. Oper. Res. 128, 282–289.
Walsh, S.T., 2004. Roadmapping a disruptive technology: a case study: the emerging microsystems and top-down nanosystems industry. Technol. Forecast. Soc. Chang. 71, 161–185.
Wang, C.-h., Lu, I.-y., Chen, C.-b., 2008. Evaluating firm technological innovation capability under uncertainty. Technovation 28, 349–363.
Wenk Jr., E., 1973. Priorities for research applicable to national needs. In: Committee on Public Engineering Policy. National Academy of Engineering, Washington, D.C..
Wenk Jr., E., Kuehn, T.J., 1977. Interinstitutional networks in technological delivery systems. In: Haberer, J. (Ed.), Science and Technology Policy: Perspectives and Developments. Lexington Books, Lexington, Massachusetts, pp. 153–175.
Zhang, Y., Porter, A.L., Hu, Z., Guo, Y., Newman, N.C., 2014. "Term clumping" for technical intelligence: a case study on dye-sensitized solar cells. Technol. Forecast. Soc. Chang. 85, 26–39.
Zhang, Y., Zhang, G., Chen, H., Porter, A.L., Zhu, D., Lu, J., 2016. Topic analysis and forecasting for science, technology and innovation: methodology with a case study focusing on big data research. Technol. Forecast. Soc. Chang. 105, 179–191.
Zhu, J., 1999. Local growth coalition: the context and implications of China's gradualist urban land reforms. Int. J. Urban Reg. Res. 23, 534–548.

Ying Huang is a Ph.D. candidate in the School of Management and Economics, Beijing Institute of Technology. He was in School of Public Policy at Georgia Tech as the visiting scholar from September, 2014, to September, 2015. His specialty is technology innovation management and technology forecasting, particularly for study of emerging technology. He is the reviewers of academic peer-reviewed journals including Technological Forecasting and Social Change, Technology Analysis & Strategic Management, Scientometrics, International Journal of Technology Management.

Alan L. **Porter** (PhD) is Professor Emeritus of Industrial & Systems Engineering, and of Public Policy, at Georgia Institute of Technology, where he remains Co-director of the Technology Policy and Assessment Center (TPAC). He is also Director of R & D for Search Technology, Inc., Norcross, GA. He is author of some 230 articles and books. Current research emphasizes measuring, mapping, and forecasting ST & I knowledge diffusion patterns.

Scott W. Cunningham (PhD) is the associate professor of Policy Analysis in the Department of Technology, Policy and Management, Delft University of Technology. He received a Ph.D. in Science, Technology and Innovation Policy from the Science Policy Research Unit. He is interested in operations research and decision sciences approaches for policy making, especially in probabilistic models of social exchange. Other interests include building multi-actor systems theory through the economic sociology and innovation policy literatures. Besides, He is the associate editors of Technological Forecasting and Social Change.

Douglas K. R. Robinson (PhD) is a researcher and consultant on the dynamics, management and policies of innovation, with a particular focus on emerging technologies. He weaves together three axes of research: the dynamics of technology emergence (particularly the collective dimension); future-oriented analyses informed by dynamics of socio-technical change; and policy and strategic intelligence on research and innovation. He has recently written reports for the OECD, NASA, ESA and the French Ministry of Research and Higher Education on emerging technologies and new industrial dynamics.

Jianhua Liu (PhD) is the associate professor of National Science Library, Chinese Academy of Sciences (CAS). Besides, she is a librarian in National Science Library CAS. She was in School of Public Policy at Georgia Tech as a visiting scholar from October 2015 to May 2016. Her research focus on information extraction and text mining.

Donghua Zhu is a professor in the School of Management and Economics, Beijing Institute of Technology, where he remains director of the Laboratory of Knowledge Management and Data Analysis. His main academic research fields include science and technology data mining, technology innovation management, technology forecasting and management. He was the main technical backbone and project designers of Department of Defense project and NSF program shouldered by Technology Policy & Assessment Centre (TPAC) in Georgia Institute of Technology.