A Systematic Method for Technology Assessment: Illustrated for 'Big Data'

Authors: Liu,Jianhua, Guo, Ying, Alan Porter, Huang,Ying, Liu,Jianhua

Date: 2016-06-12T00:00:00+00:00

Abstract

Technology assessment is a systematic examination of the effects on or of new developments such as technologies, processes, policies, organizations, and so on. In this paper, we present a systematic method for technology assessment, as a part of the suite of tools for Forecasting Innovation Pathways (FIP). We explore means to combine tech mining tools with human intelligence in several idea exchange rounds to uncover potential secondary effects, and array them in terms of likelihood and magnitude. Big Data is studied as the case study. This is on-going research. We are currently on the 2nd round of stage 2. Technology assessment is a necessary component of FIP. It identifies areas in which significant impacts may occur, their likelihood, and their significance. The forecaster must evaluate these impacts, consider measures to enhance or inhibit them, and factor them into the planning process for developing the technology.

Full Text

Preamble

A Systematic Method for Technology Assessment: Illustrated for 'Big Data'

Jianhua Liu[1], Ying Guo[2], Alan Porter[3], Ying Huang[2]
[1]National Science Library, Chinese Academy of Sciences, Beijing, 100190, China
[2]School of Management and Economics, Beijing Institute of Technology, Beijing, 100081, China
[3]School of Public Policy, Georgia Institute of Technology, Atlanta (USA), and Search Technology, Inc., Norcross, Atlanta, GA 30092, USA

Abstract: Technology assessment is a systematic examination of the effects on or of new developments such as technologies, processes, policies, organizations, and so on. In this paper, we present a systematic method for technology assessment as part of the suite of tools for Forecasting Innovation Pathways (FIP). We

explore means to combine tech mining tools with human intelligence through several idea exchange rounds to uncover potential secondary effects and array them in terms of likelihood and magnitude. Big Data is studied as a case in point. This is ongoing research; we are currently in the second round of Stage 2. Technology assessment is a necessary component of FIP. It identifies areas in which significant impacts may occur, their likelihood, and their significance. The forecaster must evaluate these impacts, consider measures to enhance or inhibit them, and factor them into the planning process for developing the technology.

I. Introduction

In recent years, we have developed a suite of tools for Forecasting Innovation Pathways (FIP). FIP builds on "tech mining" [**?**, **?**], especially analysis of global database search results on the technology under study. Robinson et al. [**?**] laid out four stages and ten steps. The third stage of the FIP approach includes "Technology Assessment." Technology Assessment (TA) has dual meanings. For one, it concerns the evaluation of alternative technologies—that is, comparing current or evolving technologies in terms of specific objectives. But TA also refers to a second, distinct set of activities—namely, "impact assessment" —studying the future broad societal effects of the development and application of emerging technologies [**?**]. The classic definition directs attention to the "unintended, indirect, and delayed" effects of such development [**?**]. That is the focus of this paper.

In FIP development to date, our TA efforts have received less attention. In this paper, we address impact identification and assessment. We develop and apply essential impact assessment aids to identify high-likelihood and/or high-magnitude effects associated with developmental choices. The paper aims for a systematic process for TA that identifies potential slow-emerging impacts quickly and efficiently: (1) address the full framework, including foundations, uses (applications), and potential impacts (both positive and negative); (2) experiment with tech mining tools to elicit indications of potential secondary effects by developing impact taxonomies; and (3) perform basic analyses of the potential effects identified to array them in terms of likelihood and magnitude—then focus attention on impacts that appear either high-likelihood and/or high-magnitude. We present those results for review and exploration of candidate mitigation measures to treat undesirable impacts, both via traditional workshops and internet-enabled modes, and compare those approaches. "Big Data" is the focus for this empirical case analysis. Big Data portends momentous implications for multiple sectors, offering a timely and rich topic for exploration of potential impacts.

II. Contextual Framework & Research Approach

Technology assessment is a meta-level method used to analyze potential development pathways of a technology and the social and economic implications of this development [?, ?]. Included in technology assessment are methods to perform empirical analysis of the emerging technology, methods to engage stakeholders, experts, and publics, and methods to assess future pathways [?]. Technology assessment does not presume to provide accurate predictions of the future. Rather, it seeks to reduce the uncertainties that restrict investment in the technology through revealing and, presumably, encouraging attention to negative societal impacts [?, ?]. Technology assessment has traditionally been a central government function (the US Congress as of 1995 no longer has an Office of Technology Assessment to study the likely impacts of new technologies, but other US organizations are involved in technology assessment, including the National Academies and the General Accountability Office (GAO)). However, decentralized methods have arisen to obtain more diverse inputs as technologies are emerging [?, ?].

Beginning in Spring 2015, with U.S. National Science Foundation (NSF) support, we have been working on "Forecasting Innovation Pathways of Big Data & Analytics." Our research has two main elements: (1) "tech mining" (empirical analyses of research funding, literature, and patents to discern R&D trends and active players), and (2) engagement of stakeholders and experts to help understand developmental prospects and likely outcomes. The paper aims toward a systematic process for impact identification, analysis, and evaluation. We seek first to identify potential impacts quickly and efficiently (the process is not linear; "effects of effects" could be important; enhanced exploration of innovation pathways should uncover additional effects). [Figure 1: see original paper] shows our Contextual Framework for Technology Assessment.

Stage 1: Understand the technology and scan for potential impacts. We aim to address the full developmental pathways—that is, consider implications of the processes as well as the resulting applications. We do so through: (1) bibliometric methods (search strategies are needed here; the database could be Web of Science, etc.). Here, we choose the ProQuest Business database, which may reflect consideration of impacts in conjunction with developing applications. (2) Literature review is also important here. For some emerging technologies, impact discussion can be very informative in reviews, foresight studies, consulting reports, etc. (3) Use of a web crawler might also help, but we have not utilized that in this study. After scanning to identify impacts, we separate the candidate impacts using select criteria—that is, by positive vs. negative; affecting organizations/individuals/society; by particular application arenas; data-driven vs. problem-driven, etc. Also, we sort the potential effects identified to array them for consideration of their likelihood and magnitude.

Stage 2: Exchange ideas and review the impacts. We strive to present those results in a concise, easily digested format for review by persons whom we have identified through our "tech mining" of databases and review of key papers and for whom we have obtained e-mail addresses. We ask them to improve our set of potential impacts of interest. Then, we digest what we hear to summarize Big Data "impact identification." Moreover, we seek open internet inputs to enrich that characterization, clarify preferences of various stakeholders, and posit policy actions warranting attention.

Stage 3: Following analysis. We pursue research to explore the impacts, seeking data to support estimations of likelihood and magnitude, identify contingencies and dependencies, identify stakeholder perspectives, etc. Policy suggestions should be the final outcomes for this Stage.

III. Illustrative Case: Big Data & Analytics

Although the legacy of information technology development is long, the term "Big Data" has a more recent history. Some trace the notion of Big Data to a special issue of *Nature* published in September 2008 on the topic, while others allude to earlier or later references. Indeed, the term itself has become a "meme" for developments in the 21st century that facilitate the procurement, storage, processing, and analysis of large-scale information compilations. Boyd and Crawford [**?**] call out the "mythology" of the term, associating it with an overly optimistic and opportunistic rhetoric. The White House [**?**] has drawn on the Gartner, Inc. definition of Big Data in terms of the three "Vs" (although more Vs have been added in other definitions): (1) volume of data collected and processed at decreasing cost; (2) variety of data, including digital data and data originating in analog forms that can be digitized (see President' s Council of Advisors on Science and Technology, 2014); and (3) velocity of data that can be obtained nearly in real-time. The ability to process more information, more quickly, and with greater ease of analysis opens up opportunities in medical, business, scientific research, environmental, defense, and climate change applications, among others [**?**]. Concerned by the great potential but also imposing impacts, GAO initiated a "21st Century Data" TA in 2015. This is being undertaken on behalf of the Comptroller General (i.e., at GAO initiative). This presents an intriguing opportunity for our Georgia Tech-based team to address this, not uncommon, gap between historical and future-oriented analyses. We propose to experiment with our Forecast Innovation Pathways methodology on this "big data & analytics" Assessment. In doing so, we will be in position to present how FIP empirical methodology can provide useful insights into innovation prospects and implications of Big Data, the "internet of things," quality and privacy issues, and such.

A. Understand the Technology & Scan the Potential Impacts

We conduct tech mining of R&D on "Big Data & Analytics" (BDA) drawn from multiple databases: Web of Science (WoS), INSPEC, ABI Inform, NSF and NSFC (National Natural Science Foundation of China) awards, and Derwent Innovation Index patents. The analyses show amazing growth in R&D and attention to BDA building hyper-exponentially from 2008, but showing indications of saturating as of 2015. A map of the publications indexed by WoS shows incredibly broad interest—extending way beyond computer and data science—in using BDA to advance research in diverse fields. Our analyses find the U.S. and China leading the global BDA effort.

Here we emphasize search results on Big Data from the ProQuest Business database for 2010-2014. We use the terms—problem/risk/challenge/impact/effect/burden/benefit —to reduce the 9,696 Big Data records to 620 that appear to consider impacts. We review topical term lists and read selected abstracts to bolster our candidate Big Data impacts set. Additionally, we read more than 60 selected articles to widen and deepen our understanding of potential impacts of the development, application, and uses of Big Data. We have identified some 20 major application areas, pursuing in-depth analyses of select ones (e.g., Electronic Health Records —EHR). Here we aspire to address impacts arising from any of the applications to help inform policy considerations.

We model Big Data applications using a simple 3-level framework ([Figure 2: see original paper]):

1. **Information Technology (IT) Foundations** -Communications, Storage, and Computing that enable Big Data functionality (Note: this level is NOT our focus here.)
2. **Analytics** -Building on the Big Data foundations, enhanced and new functionality is coming into use. We perceive four major functional elements: monitoring; modeling & prediction; auditing & evaluation; and process optimization.
3. **Uses, especially oriented to decision support** -including four prominent forms: service improvement; management & organization; process improvement; and R&D.

We then separate the candidate impacts using select criteria—that is, positive vs. negative; affecting organizations/individuals/society; by particular application arenas; data-driven vs. problem-driven, etc. tracks how functions (Column 1) could be operationalized (Column 2), leading to Uses (Column 3). Column 4 adds example impacts. Our focus is on the U.S., with an eye toward potential Federal policy actions to promote beneficial development while reducing potential risks and costs.

As mentioned, we undertake analyses at two levels for Big Data. At a general level, we seek to identify notable systemic characteristics and effects of Big Data for many applications, targeting impacts not limited to a particular application domain. Second, for specific applications, we focus on one application domain and perform a similar TA process (the EHR impact table is not shown here).

B. Exchange Ideas & Renew the Impacts

First Round: We identified about 50 persons through tech mining of databases and review of key papers, and obtained e-mail addresses for them. In the emails we sent, we laid out our research pursuits and directed them to the project webpage (http://bigdatagt.org). We sent them Figure 2 and Table 1 to illustrate our understanding of Big Data and welcomed their refinements to any of that content, but expressly sought suggestions regarding potential indirect, delayed, or unintended effects (Column 4 of Table 1). The grey blank cells in Table 1 invited any additional points they might offer. We also welcomed ideas on possible policy and mitigation options to deter undesirable effects. We sent a reminder 10 days after the first-round emails. We digested the feedback to update Table 1 and summarize our initial "impact identification." Unfortunately, the response rate has been low (~12%), consistent with other email surveying our Center has done recently. The weak response prods us to pursue alternative internet-based methods to engage various interested parties. We are pursuing a blog model, providing easy means to stay in touch with interested parties and attract their feedback (we will update results at PICMET).

Second Round: As noted, we are creating a blog to seek open internet inputs to enrich our characterization of Big Data implications, clarify preferences of various stakeholders, and posit policy actions warranting attention. We'd like to get two types of responses—invited (by us) and open (anyone). We invite the 50 reviewers from the first round to engage the website. We share detailed project descriptions and bibliometric analysis results there, as well as the revised impact table (Table 1 in this paper) according to reviewers' comments. The website is also open to the public. Our plan is to track inputs from various invitees versus those from open comment to check for discrepant estimates and valuations.

More importantly, we aim to understand the likelihood and magnitude of each impact. We have drawn sets of major impacts () from Table 1 and defined each impact briefly. We'd like to have three responses for each impact: (1) percentage (likelihood); (2) importance (magnitude); (3) policy action suggestions. We ask for a likelihood of occurrence in the year 2026 (10 years from now). As a contingent question, we also ask: if that impact does occur, how large an effect will it exert on the US?

For example: - **Q1:** One possible outcome of widespread BDA application could be displacement of analysts in many sectors. How likely do you think that BDA will significantly displace American analysts by the year 2026? [0-10] - **Q2:** If such displacement occurs, out of some X million analysts working today, what would be the net reduction due to BDA as of 2026? [in millions; with option of increase instead of decrease] [0-10] - **Q3:** Any policy action suggestions under such a situation?

We have created a model 2×2 matrix—BDA Impact Estimation—to show the likelihood and magnitude survey results about potential BDA effects. This axis shows 0-10 scaling on Likelihood (vertical axis) and 0-10 on Magnitude (horizontal axis) of each effect, with grid origin at (5,5). Drawing on literature, discussion, and knowledgeable feedback, we have identified 20 candidate impacts (i.e., outcomes or effects) of widening uses of Big Data Analytics over the coming 10 years. We want to locate these on a 4-quadrant chart to help identify the most important effects that warrant possible policy actions to encourage or reduce. [Figure 3: see original paper] illustrates several effects in this chart to stimulate consideration of likelihood and magnitude.

IV. Discussion

Technology assessment is a systematic examination of the effects on or of new developments such as technologies, processes, policies, organizations, and so on. Impact assessments are classified as policy studies, since they can affect the policies of the organizations that conduct them, as well as those of other stakeholders. In most cases, impact assessments should result in actions. Assessments may be freestanding or part of another study such as a technology forecast. We are working to develop a systematic system to help conduct technology assessment, in which the third stage (to finish pre-PICMET) targets policy action analysis. Combining the empirically-based work at which we excel, we emphasize interactions with experts and publics via internet modes in this study.

In this paper, we focus on our early attempts to build a systematic system for technology assessment. Our goal is to identify and assess the unintended, indirect, and delayed impacts through this system. This approach combines quantitative and qualitative analyses. This BDA analysis was a small-scale experiment. By inviting people to join the impact analysis discussion, such work could bolster development of the technology itself. This type of information interchange could actively contribute to that development by helping to coalesce visions of innovation targets, identify obstacles to be overcome and assets upon which to draw, and perform impact assessment to identify potential beneficial and harmful effects.

Acknowledgment

We acknowledge support from the US National Science Foundation (Award #1527370 –"Forecasting Innovation Pathways of Big Data & Analytics"). The findings and observations contained in this project are those of the authors and do not necessarily reflect the views of the National Science Foundation.

Thanks for review and suggestions: Sanjay Arora (Georgia Tech); Laura Haas (IBM); James Cooper (George Mason University School of Law); Muhammad Anshari (University Brunei Darussalam, Continuing Education Centre & e-Government Innovation Centre); Michael Rappa (North Carolina State University); Dan Suciu (University of Washington)

References

[1] Porter AL, Cunningham SW (2005) *Tech mining: exploiting new technologies for competitive advantage*. Wiley, New York

[2] Porter, A.L., and Newman, N.C. 2011. Mining External R&D, *Technovation*, 31, 171-176.

[3] Robinson, D. K., Huang, L., Guo, Y., & Porter, A. L. (2013). Forecasting Innovation Pathways (FIP) for new and emerging science and technologies. *Technological Forecasting and Social Change*, 80(2), 267-285.

[5] Coates, J.F. (1976), Technology Assessment -A Tool Kit, *Chemtech* (June), 372-383.

[6] Porter, A.L., Rossini, F.A., Carpenter, S.R. and Roper, A.T. (1980). *Assessment and Impact Analysis*. New York: North Holland.

[7] Rip, A. and TeKulve, H. (2008). Constructive Technology Assessment and Socio-Technical Scenarios. *The Yearbook of Nanotechnology in Society*, Volume 1: Presenting Futures. E. Fisher, C. Selin and J. M. Wetmore, Springer: 49-70.

[8] Porter, A.L., Ashton, B., Clar, G., Coates, J., Cuhls, K., Cunningham, et al. (2004). Technology futures analysis: Toward integration of the field and new methods. *Technological Forecasting & Social Change*, 71(3), 287-303.

[9] Hoppe, H. C. (2002). The Timing of New Technology Adoption: Theoretical Models and Empirical Evidence. *The Manchester School*, 70: 56–76.

[10] Robinson, D. K.R., Le Masson, P., Weil, B. (2012). Waiting games: innovation impasses in situations of high uncertainty. *Technology Analysis & Strategic Management*, 24(6), 543-547.

[11] Guston, D. H., Sarewitz, D. (2002). Real-time technology assessment. *Technology in society*, 24(1)

[12] Kuhlmann, S. (2001). Future governance of innovation policy in Europe—three scenarios. *Research Policy*, 30(6), 953-976.

[13] Boyd, D., Crawford, K. (2012). Critical questions for big data: Provocations for a cultural, technological, and scholarly phenomenon. *Information, communication & society*, 15(5), 662-679.

[14] Bryant, R., Katz, R. H., Lazowska, E. D. (2008). Big-data computing: creating revolutionary breakthroughs in commerce, science and society.

[15] Rousseau, R. (2012). A view on "big data" and its relation to Informetrics. *Chinese Journal of Library and Information Science*, 5(3), 12-26.

Rotolo, D., Hicks, D., Martin, B. (2015). What is an emerging technology? *Research Policy* 44(10),

White House (2014). *Big Data: Seizing Opportunities, Preserving Values.*

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