Strategies and Influencing Factors for Big Data Exploration

Full Paper

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Abstract

Many enterprises feel the need to explore the possibilities big data may provide for their business. However, they hesitate to apply big data, as they are unsure how to successfully identify new opportunities. We analyze in a multiple case study how companies start to investigate big data applications. Based on these case studies, we find two generic strategies companies tend to follow. These strategies focus either on the search for potential business opportunities or on the need to develop technology infrastructure. In order to understand the strategy selection, we utilize the Technology-Organization-Environment (TOE) framework. Our findings are twofold. First, we identify factors that influence the choice of strategy. Second, we identify the factors that influence the initiation phase of big data adoption within a chosen strategy.

Keywords

Big Data, Big Data Adoption, Technology Organization Environment Framework.

Introduction

Big data promises new data driven services to improve products, services or processes of companies from all industries (see e.g. Jukić et al. 2015; Sivaraja 2017). Although many enterprises feel the need to explore the possibilities big data provides for their business, they hesitate to apply big data as they are unsure how to start and how to successfully identify new business opportunities. These questions concern many companies. For example, a research from Gartner reports that 82% of companies are still experimenting with big data, developing strategies or gathering knowledge (Gartner 2015). Only 14% have put big data projects into production. Apparently, the productive use of big data technologies is still low, compared to the interest in the topic. Therefore studies of big data adoption are interesting and important.

Innovation adoption is often described by three major phases (Rogers 2003; Damanpour and Schneider 2006): initiation, adoption and implementation. Along this path new technologies have to overcome several hurdles before being used productively. For technology driven innovations, like big data, the starting phase, where enterprises search for valuable use cases and applications leveraging new possibilities, poses a first serious obstacle. This initial step towards a successful adoption is the focus of our research.

This paper studies several cases on how companies start exploring big data. In particular we utilize the Technology-Organization-Environment (TOE) framework (Tornatzky and Fleischer 1990) to investigate the initiation phase of big data adoption. Based on the reported case studies, we find two generic strategies that are pursued by organizations. These strategies focus either on the search for potential business opportunities or on the need to develop technology infrastructure. The use of the TOE helps to understand these strategies and their determinants: We first identify and classify factors that influence the choice of strategy. Second, we recognize factors with major influence on the initiation phase of big data adoption within a chosen strategy.

Our results are based on a multiple case study. Our main information sources are in-depth expert interviews with key-informants. For the explanation of our results we use the TOE (Tornatzky and Fleischer 1990) adapted from existing big data adoption studies (Malaka and Brown 2015; Agrawal 2015; Nam et al. 2015).

This report is organized as follows: Current research on big data adoption is summarized in the next section. In section three, we sketch our conceptual model based on TOE and existing big data adoption models. Our research design is introduced in the fourth section. The results of our cases are described and discussed in the last sections of this paper.

Current Research on Big Data Adoption

In accordance with many other definitions, the TechAmerica Foundation states (TechAmerica 2012) "big data is a term that describes large volumes of high velocity, complex and variable data that require advanced techniques and technologies to enable the capture, storage, distribution, management, and analysis of the information." Obviously, there are ambiguities about limits on the three Vs – volume, variety and velocity – that define big data. However, for every company a "three-V tipping point" exists beyond which traditional data management and analysis technologies become inadequate for deriving intelligence within a sufficient period of time. This tipping point poses a threshold beyond which firms start dealing with big data and examine the value of new technologies compared with their present implementations (Gandomi and Haider 2015).

Regardless of the ambiguities about the onset of big data, researchers and business people agree that big data has the potential to answer new and complex analytical questions and provides information insight that would have been concealed by conventional analysis methods (Boyd and Crawford 2012). In order to unlock this potential, companies have to acquire big data resources and develop capabilities to leverage their possibilities (Mikalef et al. 2016). The literature defines three key typologies of big data capabilities (see e.g. Akter et al. 2016): management capabilities (e.g. data governance), technology capabilities (e.g. integrating and operating Hadoop components) and talent capabilities (e.g. data science knowledge).

The introduction of innovations in companies – such as big data – which eventually leads to the development and deployment of corresponding capabilities, is described by innovation adoption processes. These can in general be divided into three typical phases: initiation, adoption (decision) and implementation (see e.g. Damanpour and Schneider 2006; Rogers 2003; Zmud 1982). During the initiation phase companies become aware of an innovation, consider its use for a recognized need and propose its adoption. In the adoption phase proposed ideas are evaluated from technical, financial and strategic perspectives. Then an adoption decision is taken, which includes the allocation of resources for the implementation and assimilation of an accepted solution. All preparations for its productive use are then carried out during the implementation phase.

Currently, the adoption of big data is discussed extensively by software vendors and IT consultancies. However, scientific research is still scarce. Nam et al. (2015) investigates the key factors that influence big data adoption in the three innovation phases. For this purpose the TOE framework has been used (Tornatzky and Fleischer 1990). It describes the impact of technological, organizational and environmental aspects on organizational decision making with respect to technology innovations. Nam et al. explore in particular the influence of direct and indirect benefits, financial readiness, information system (IS) competence as well as industrial and government pressure. As main results they find, that the initiation phase of the innovation process is positively affected most by IS competence. Industry pressure and perceived direct benefits also seem to be important, however with smaller impact. The adoption phase is driven by industry pressure while the implementation stage is mostly influenced by IS competence and financial readiness. Different approaches to big data adoption and their relation to TOE aspects have not been investigated.

The TOE was also utilized by Malaka and Brown (2015), who studied the adoption of big data analytics within the telecommunication industry in South Africa. They identified major challenges and mapped them to the three perspectives of the TOE. Technological challenges found were data integration, data privacy, return on investment, data quality, cost, data integrity, performance and scalability. Major challenges from an organizational perspective were ownership and control, skills shortages, business focus and prioritization, training, organizational silos and unclear processes. From the environmental context no major challenges were highlighted. Organizational aspects were recognized as the major inhibitors to adoption. An examination of the different phases of the adoption process has not been pursued.

The approach of Agrawal (2015) is quite similar. He used the TOE to explore the high-level determinants that influence the adoption of big data analytics in emerging economies. The innovation process was considered in its entirety, without distinguishing different phases. As a result the six variables complexity, compatibility, regulatory support, organizational size, competition intensity and environmental uncertainty were found to be significant determinants. Of those regulatory support and complexity were inhibitors and most influential, all other factors were facilitators of adoption.

Similar factors influencing big data adoption have been found recently also in a content analysis based on research publications in the business intelligence and analytics literature by Sun et al. (2016).

Chen et al. (2015) used a multiple case study to obtain a more detailed view on big data adoption processes and corresponding influencing factors. As a result, they describe several steps within the three phases of the innovation adoption process from Rogers et al. (2003). TOE, Diffusion of Innovation (DOI) (Rogers 2003) and IT Fashion Theory (Wang 2010) were used as sources for influence factors. From DOI, which describes the process of spreading an IT innovation among the members of a social system, one obtains relative advantage, compatibility, complexity, observability and trialability as important attributes. The IT Fashion Theory on the other hand provides aspects that highlight the social settings of emerging IT trends. In particular, it includes the influence of fashion-setters like consultants and technology analysts. Chen et al. extend the aspects of these theories by including organizational, environmental, social variables as well psychological factors. They found that relative advantage is a necessary but not sufficient condition for big data adoption. As a central result, they uncovered a so called "Deployment Gap" and a "Limbo Stage", where companies continuously experiment for a long time with big data technologies and do not proceed to deployment despite the intent to adopt. While this research sheds light on the later stages of big data adoption, details and strategies for its starting phase have not been explored.

In comparison to existing studies our research focuses on the initial phase of big data adoption. We investigate the strategies companies use to approach big data and the factors influencing their choice. With respect to the innovation adoption processes, we explore in particular the initiation phase. It includes the identification of potential application areas and use cases. If – at the end of this phase – the intention to adopt a specific big data use case is high, organizations propose its adoption. They then proceed with a thorough evaluation, including e.g. prototyping, and implementation activities. These later steps are studied, e.g., in Chen et al. (2015) and not focus of this paper.

Conceptual Framework

The goal of this research is to identify how companies approach big data, what strategy they use, and whether there are factors that have a significant impact on their choice of strategy. For this purpose, we use the TOE framework (Tornatzky and Fleischer 1990). It describes the main factors influencing the adoption of technology innovations. These factors are clustered into three dimensions: technology, organization and environment.

The technology dimension encompasses the characteristics of available technologies which are relevant to a company. The organizational dimension covers company attributes, such as size, formal and informal linking structures, competencies and the amount of slack resources. The company's environment and its influence are described in the environmental dimension. It includes competitors, industry specifics and governmental regulation. The main strength of the TOE framework is its adaptability and the freedom to vary the factors or measures for each new research context (Baker 2011). As a consequence the TOE is extensively used in adoption research (for examples see e.g. Baker 2011; Oliveira 2011). Central to most of these studies is the identification and classification of factors that influence the adoption of a certain technology as well as their interplay. The TOE has also been applied to big data adoption as summarized in the previous section. The corresponding results for influencing factors are shown in Table 1. As already mentioned, they have been related to the entire adoption process.

Dimension	Malaka, Brown (2015)	Agrawal (2015)	Nam et al. (2015)
Environment	- Industry/market competition - Vendor reliance - Data security & privacy	- Environmental uncertainty - Competition intensity - Regulatory support	- Perceived industry pressure - Perceived government pressure
Technology	- Time and cost - Data integration - Veracity - Performance & scalability	- Complexity - Compatibility - Relative advantage	- Perceived direct benefit - Perceived indirect benefit
Organization	- Ownership and control - Skill shortage - Communication processes	- Technological resource competency - Organizational size - Absorptive capacity	- Perceived financial readiness - Perceived IS competence

Table 1. Influencing factors of big data adoption studies

For our investigation of the initiation phase of big data adoption and the corresponding strategies and influence factors, we use the TOE as a conceptual framework, including the factors from Table 1 as a starting point. The goal of our study is twofold: First, we identify the factors which drive the strategy companies currently use to approach the potentials of big data. Second, we recognize the factors with major influence on the initiation phase of big data adoption within a chosen strategy.

Research Design

Phenomena around big data adoption are complex and certainly not well understood so far, thus a case study approach is suitable (Yin 2003). We chose a multiple case design to support the generalizability of results (Dubé and Paré 2003; Yin 2003).

Our main information sources are in-depth expert interviews with key-informants (Bagozzi et al. 1991). Interviewees were heads of business and IT divisions, chief architects and chief strategist. In addition to the interviews, we collected available public and corporate information about big data initiatives of participating companies.

The expert interviews were semi-structured. The interviews covered all dimensions of the TOE described in the previous section. We kept our questions open to allow interviewees freely to speak. The first part contains general questions about the role and responsibility of the interviewee, the current strategic and tactical challenges of the company and their influence upon dealing with new possibilities of big data. The second part of our questions concentrates on the current use of data, methods and technologies for data-driven decision making as well as corresponding organizational structures and processes. For example, we asked about the relevance of data and data-driven decision making in different organizations and inquired which kind of analytical applications were in use currently. The third and most extensive set of questions was directed upon “why” and “how” organizations explore the potentials of big data. These questions concerned the trigger of big data initiatives, their focus and their organizational setup. Also we inquired the process for the evaluation of big data potentials and the criteria applied therein.

The selection of cases follows a literal replication logic (Dubé and Paré 2003) to ensure comparable organizational and technological contexts. We have investigated cases from ten companies. Our focus was on large companies with more than 10,000 employees with their headquarters in Germany and operating internationally. Pure internet companies were excluded. To obtain insights into sector-specific variations, the cases cover different types of industries, including transportation, banking, insurance, manufacturing, pharma, retail and utilities.

Every interview lasted approximately 90 minutes. The interviews were recorded and transcribed. The data collection started in June 2016 and stretched over a period of seven months. Shortly after each interview, the main points and key findings were recapitulated in a contact summary sheet. The interviews were then analyzed and coded. We used first-level coding (Miles et al. 2014) to identify in particular all statements related to company's procedures for big data exploration, the goals of their initial activities and corresponding influence factors. The collected company documents and information were used to triangulate our findings. Furthermore, we established a case study database to minimize errors and biases (Yin 2003) and stored all information about the data collection process, the data itself and the case study results into the database. According to Yin (2003), this helps to provide the same results on repeated trials.

Results from Case Studies

An overview of the analyzed cases is given in Table 2. The companies operate in B2B as well as in B2C segments. The interviewees had roles in business and IT.

	Industry	Number of employees	Business segment	Role of Interviewee
1	Transport	>50,000	B2C, B2B	Head of Domain Architecture
2	Banking	>50,000	B2C, B2B	Head of IT Architecture
3	Insurance	>10,000	B2C, B2B	Head of Group strategy
4	Manufacturing Vehicle	>50,000	B2B	IS Chief-Architect
5	Retail Trade	>50,000	B2C	Head of Business Intelligence
6	Utilities	>50,000	B2C, B2B	Chief Digital IT Strategist
7	Manufacturing Vehicle	>50,000	B2B	Head of Analytics Lab
8	Manufacturing Apparel	>50,000	B2C	Head of Data Analytics Lab
9	Manufacturing CPG	>10,000	B2C	Head of Marketing & Analytics
10	Manufacturing Chemicals	>10,000	B2B	Head of BI Architecture

Table 2. Companies participating in analysis

The results of our cases are based on a twofold analysis and are summarized in Table 3 and 4. First, we conducted a within-case analysis to extract aspects which were mentioned as main factors influencing the current big data activities of companies. These are listed as case characteristics. We also extracted information regarding big data activities and goals during the initiation phase, when firms initially explore big data potentials. These are also included in Table 3 and 4. After we conducted the within-case analysis, we used a cross-case analysis to search for similarities and differences or patterns in the cases. While conducting this analysis, two different strategies for approaching big data potentials became apparent:

Business first (Table 3): Organizations in this category explore big data potentials entirely from a business perspective. They search for use cases with high expected business value. These use cases span from possible improvements of existing processes to entirely new business services or business models. Investigations of the required effort for corresponding implementations into the productive IT landscape are postponed to a later stage. For example in case 1 the transportation company established innovation units staffed mainly with people from business departments to search for promising use cases with high business value. Studies of constraints from a technical or data management perspective were excluded in this phase.

Case	Case Characteristics	Explorative Big Data Activities & Goals
1	- strong competition from low cost players, falling prices and volatile commodity markets - big data as part of digital strategy, management support, dedicated resources, e.g. innovation units, data labs - expected benefits in process optimizations and new business services for travelers - complexity is not considered during the initiation phase	establish innovation units; fast validation of business cases for ideas in lab environment; focus on process optimizations and new business services
6	- deregulated market and energy transition causes uncertainties - data-driven company is long-term goal and big data initiatives are driven by top management - benefits are expected for customer retention and through new digital products, e.g. for smart meters - high BI maturity and the availability of IS resources supports the development of new data-driven products	search for digital product ideas; agile and fast product development in data labs; data-driven validation of products in market
8	- big data is placed as a mega trend by top management - operational efficiency is seen as key challenge in a highly competitive global fashion market; its improvement is focus of first activities - BI maturity is high - high perceived complexity of available technologies and lack of external available knowledge	establish lab environment, develop big data show cases for organization; focus on operational efficiency
9	- market is characterized by aggressive trade groups firing up competition and economic uncertainties, e.g. brexit votum - integrated and harmonized data architecture exists - benefits are expected in particular in the area of promotional efficiency - new technologies are explored through external providers	integrate additional data sources; expand data hub; strengthen promotional efficiency

Table 3. Overview of cases using business first

Platform building (Table 4): These organizations initially focus on an identification of key activities for the development of a future-oriented big data platform and not on the search for particular business applications. Their goal is to lower the barrier for a later implementation of big data use cases. Specific application scenarios do not yet exist, but are expected to come up eventually. For example in case 2 a company from the banking industry started to meet existing requirements without relation to big data use cases through an implementation of new big data technologies. They introduced Hadoop components for a standard storage system and improved data integration capabilities. Both will help future big data use cases – so their assumption.

Case	Case Characteristics	Explorative Big Data Activities & Goals
2	- cost pressure through low interest rates, new competitors (e.g. fintechs), strong regulatory measures - regulatory requirements block IT resources - new technologies (e.g. blockchain), changing customer expectation - transformation of business model and new digital strategy - missing central data warehouse and issues in data quality - benefits are seen in e.g. optimized risk management, fraud detection	realize existing requirements with new technologies; systematic development of a data lake; improve data integration and lower barrier for big data use cases

3	- new technologies (e.g. autonomous driving) and ongoing low-interest rates attack existing business - potential conflicts between new data services and anticipated customer privacy - missing top management support, missing digital strategy and complexity of available technologies block use case exploration although financial readiness is given - IT resources are fully utilized by ongoing operations	set up working groups; explore requirements from straw men use cases for organization, data and technologies; identification of key activities to prepare platform
4	- competitors from emerging markets causes cost pressure, decreasing profit margins - fragmented data architecture and large number of systems lead to hurdles in organizational performance management - new top management emphasizes data-driven decision-making - benefits like process optimization are expected but the complexity of big data technologies is perceived as high, therefore basic data management & BI tasks are addressed first	rise BI maturity; set up data lab to test feasibility of performance KPIs; improve operational efficiency
5	- non-traditional competitors like Amazon increase competition in a market with low profit margins - data is seen as an asset, BI maturity is high - big data is seen as just another set of technologies - complexity challenges of new technologies is outsourced - no obvious big data use cases with additional benefits	continuous exploration of new technologies; optimize business processes and improve understanding of customer
7	- regulatory measures, e.g. driving safety and emission reduction - data is distributed over different production sites and systems - big data is perceived as complex, therefore data lab focuses on approaching analytics and developing decision documents for the management - big data is part of a formulated strategy	establish lab environment; explore requirements for big data; harmonize data & increase efficiency of operational processes
10	- increasing regulatory measures in human healthcare causes cost pressure and drive the utilization of IT - global market is consolidating as a result of strong competition - a digital strategy has been recently launched - self-service BI is widely used, BI maturity is high - data governance in big data environments is perceived as complex, therefore a systematic exploration of technologies appears appropriate	explore technological and organizational requirements of big data; systematic development of a data lake; exploration of new data based revenue streams

Table 4. Overview of cases using platform building

Discussion

Following the TOE framework we collect all influencing factors from the investigated cases and assign them to the different TOE dimensions. The result is shown in Table 5, including brief comments and explanations. As compared to previous applications of TOE to big data (Malaka and Brown 2015; Agrawal 2015; Nam et al. 2015) a company's strategy or support by top management was found as an additional influencing factor (see e.g. cases 3, 6, 8) within the organizational dimension of TOE. This aspect was also recognized for BI adoption (see e.g. Hung et al. 2016).

Technology	Organization	Environment
- benefits (value for business processes and models) - compatibility (fit to existing technologies, processes or culture) - complexity (many components with multiple ways to combine and use)	- IS competence (competence of IT usage and IT management in an organization) - financial readiness (availability of financial resources) - strategic readiness (big data is part of strategy, supported by top management)	- competitive pressure (new competitors, disruptive business models) - environmental uncertainty (volatile markets, changing customer expectations) - regulatory measures (energy transition, emission reduction, finance regulatory)

Table 5. Overview of TOE categories

Table 6 shows the factors which had the main influence on a company's choice of strategy for approaching big data – i.e. business first or platform building. Here the environment dimension as well as benefits and compatibility from the technology dimension are absent. Factors in the environment dimension and potential benefits of big data technologies always motivated investigations of their potentials, but where not acting differently for both strategies. Also compatibility aspects did not affect the strategy choice.

	complexity	IS competence	financial readiness	strategic readiness
1		▲	▲	▲
6		▲	▲	▲
8			▲	▲
9			▲	
2		▲	▲	
3	▲			▲
4	▲	▲	▲	
5		▲		
7	▲	▲	▲	
10		▲	▲	

Table 6. Major influence factors

We found that organizations choose business first as strategy, when at least financial readiness is given. It empowers them either to establish own lab environments for the investigation of use cases, or to engage external partners to do so. IS competences for big data and strategic readiness also support this strategy. For example, the management of the manufacturing company in case 8 placed big data as a megatrend and formulated a corresponding strategy. Their financial readiness allowed them to establish a lab environment and to allocate IS resources. Another example is the manufacturing company in case 9. Here no appropriate internal IS resources were available. However financial readiness enabled the organization to search for use cases and to commission external partners to carry out proof of concept projects.

Contrary to business first, companies who follow platform building are typically influenced by a lack of financial readiness. In our cases, this was mostly caused by cost pressure through strong competition or high regulatory measures. Regulatory measures also led to an increase of corresponding IT demands and a strong utilization of IT resources. These factors prevented organizations to establish lab environments for big data or to commission external partners. Case 2 and 10 are typical examples.

Companies choosing platform building as their strategy also perceive the complexity of big data often as high and have lack of needed IS competencies. In case 4 and 7, a shortage of IS competences was signaled by a low BI maturity. Building up basic IS capabilities for big data, e.g. for data integration, is often done by straw men use cases (see e.g. case 3). These are industry-typical use cases (e.g. fraud detection in financial industry), which are leveraged to capture and analyze essential big data requirements. Missing top management support, as in case 3, also increases the preference for platform building.

Besides the identification of factors that drive the strategy how companies approach the potentials of big data, we were able to recognize factors in the TOE with major influence on the initiation phase of big data adoption within a chosen strategy.

We found that organizations following the strategy business first were mainly driven by expected benefits – the influencing factor within technology dimension of TOE. Their search for use cases fully focuses on potential business benefits of big data use cases and their underlying technology. Possible challenges with respect to compatibility, when e.g. integrating a new big data application into existing IT systems, are investigated after a clear indication of business value. They are evaluated when the organization propose a use case for adoption – i.e. after the initiation phase of technology innovation adoption.

Organizations following the strategy platform building focus on building a big data platform that can serve eventually upcoming use cases. The most relevant TOE factors for these efforts are: IS competence, complexity and financial readiness. Developing big data capabilities will enhance IS competence and will reduce complexity. As a consequence, the cost for a future evaluation and introduction of big data use cases become more favorable with respect to a given level of financial readiness.

Summary

In this paper we have investigated through an analysis of ten cases how companies start exploring big data potentials. We found that companies use two strategies to approach big data adoption. They either focus on use cases with a high potential business case, or on developing capabilities for future big data platforms. The choice of strategy can be described by external and internal influence factors within the technology, organization and environment dimensions of the TOE framework.

In particular we found that the organizational dimension of the TOE has a major influence on the choice of strategy. The availability of IS competence, financial and strategic readiness determine whether organizations choose business first or platform building. A perceived complexity of the technology dimension supports this choice.

Within a chosen strategy, we were able to observe that organizations are either driven by the technology, or by the organization dimension of the TOE. The technology dimension and its benefit aspect could be identified as main driver within the strategy business first. Organizations following this strategy are searching for use cases with high business value. We also found that organizations following platform building are driven by the organizational dimension of the TOE. They make efforts to establish IS competences and reduce the complexity of big data technologies. In this way they lower the hurdle for an eventual adoption of big data applications.

REFERENCES

Agrawal, K. 2015. “Investigating the Determinants of Big Data Analytics (BDA) Adoption in Asian Emerging Economies,” *Academy of Management Proceedings* (2015:1), pp. 1–18.

Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., and Childe, S. J. 2016. “How to Improve Firm Performance Using Big Data Analytics Capability and Business Strategy Alignment?,” *International Journal of Production Economics* (182), pp. 113–131.

Baker, J. 2012. “The Technology-Organization-Environment Framework,” in *Information Systems Theory: Explaining and Predicting Our Digital Society,* Y. K. Dwivedi, M. R. Wade, and S. L. Schneberger (eds.), New York, NY: Springer New York, pp. 231–245.

Bagozzi, R. P., Yi, Y., and Phillips, L. W. 1991. “Assessing Construct Validity in Organizational Research,” *Administrative Science Quarterly* (36:3), pp. 421-458.

Boyd, D., and Crawford, K. 2012. “Critical Questions for Big Data: Provocations for a Cultural, Technological, and Scholarly Phenomenon,” *Information, Communication & Society* (15:5), pp. 662-679.

Chen, H. M., Kazman, R., and Matthes, F. 2015. "Demystifying Big Data Adoption: Beyond IT Fashion and Relative Advantage," in *Proceedings of Pre-ICIS (International Conference on Information System) DIGIT Workshop*.

Damanpour, F., and Schneider, M. 2006. "Phases of the Adoption of Innovation in Organizations: Effects of Environment, Organization and Top Managers," *British Journal of Management* (17:3), pp. 215–236.

Dubé, L., and Paré, G. 2003. "Rigor in Information Systems Positivist Case Research: Current Practices, Trends, and Recommendations," *MIS Quarterly* (27:4), pp. 597-636.

Gandomi, A., and Haider, M. 2015. "Beyond the Hype: Big Data Concepts, Methods, and Analytics," *International Journal of Information Management* (35:2), pp. 137–144.

Gartner 2015. "Big Data Industry Insights," Available at http://www.gartner.com/webinar/3087726.

Hung, S., Huang, Y., Lin, C., Chen, K., and Tarn, J. M. 2016. "Factors Influencing Business Intelligence Systems Implementation Success in the Enterprises," in *Proceedings of Pacific Asia Conference on Information Systems 2016*.

Jukić, N., Sharma, A., Nestorov, S., and Jukić, B. 2015. "Augmenting Data Warehouses with Big Data," *Information Systems Management* (32:3), pp. 200-209.

Malaka, I., and Brown, I. 2015. "Challenges to the Organisational Adoption of Big Data Analytics: A Case Study in the South African Telecommunications Industry," in *Proceedings of the Annual Research Conference on South African Institute of Computer Scientists and Information Technologists 2015*.

Mikalef, P., Ilias, P. O., Giannakos, M., Krogstie, J., and Lekakos, G. 2016. "Big Data and Strategy: A Research Framework," in *Proceedings of Mediterranean Conference on Information Systems 2016*.

Miles, B. M., Huberman, A. M., and Saldana, J. S. 2014. *Qualitative Data Analysis,* Los Angeles, CA: SAGE Publications.

Nam, D., Kang, D., and Kim, S. H. 2015. "Process of Big Data Analysis Adoption: Defining Big Data as a new IS Innovation and Examining Factors Affecting the Process," in *Proceedings of Hawaii International Conference on System Science 2015,* pp. 4792-4801.

Oliveira, T., and Martins, M. 2011. "Literature Review of Information Technology Adoption Models at Firm Level," *Electronic Journal of Information Systems Evaluation* (14:1), pp. 110–121.

Rogers, E. M. 2003. *Diffusion of Innovations*, New York, NY: Free Press.

Sivarajah, U., Kamal, M. M., Irani, Z., and Weerakkody, V. 2017. "Critical Analysis of Big Data Challenges and Analytical Methods," *Journal of Business Research* (70), pp. 263-286.

Sun, S., Cegielski, C., Jia, L., and Hall, D. 2016. "Understanding the Factors Affecting the Organizational Adoption of Big Data", *Journal of Computer Information Systems*, pp. 1-11.

TechAmerica Foundation's Federal Big Data Commission 2012. "Demystifying Big Data: A Practical Guide to Transforming the Business of Government," Available at https://www.attain.com/sites/default/files/take-aways-pdf/Solutions_Demystifying%20Big%20Data%20-%20A%20Practical%20Guide%20To%20Transforming%20The%20Business%20Of%20GovernmGov.pdf

Tornatzky, L. G., and Fleischer, M. 1990. *The Processes of Technological Innovation*, Lexington, MA: Lexington Books.

Wang, P. 2010. "Chasing the Hottest IT: Effects of Information Technology Fashion on Organizations," *MIS Quarterly (*34:1), pp. 63-85.

Yin, R. K. 2003. *Case Study Research: Design and Methods*, New York, NY: SAGE Publications.

Zmud, R. W. 1982. "Diffusion of Modern Software Practices: Influence of Centralization and Formalization," *Management Science* (28:12), pp. 1421-1431.