Association for Information Systems
AIS Electronic Library (AISeL)

Proceedings of the 2016 Pre-ICIS SIGDSA/IFIP WG8.3 Symposium: Innovations in Data Analytics

Special Interest Group on Decision Support and Analytics (SIGDSA)

12-11-2016

Towards a Framework for Open Data Related Innovation Contests

Barbara Dinter
Chair of Information Systems, Chemnitz University of Technology, Chemnitz, Germany., barbara.dinter@wirtschaft.tu-chemnitz.de

Christoph Kollwitz
Chemnitz University of Technology, christoph.kollwitz@wirtschaft.tu-chemnitz.de

Towards a Framework for Open Data Related Innovation Contests

Research-in-Progress

Barbara Dinter
Chemnitz University of Technology
Chemnitz, Germany
barbara.dinter@wirtschaft.tu-chemnitz.de

Christoph Kollwitz
Chemnitz University of Technology
Chemnitz, Germany
christoph.kollwitz@wirtschaft.tu-chemnitz.de

Abstract

Open data is considered as a promising resource for innovation, in particular in light of the ongoing digitization of society and economy. Currently, organizations lack of knowledge and skills to make efficient use of this resource. Based on the theoretical underpinning of absorptive capacity, the paper investigates how organizations could be supported by using open data for innovation. Following the design science research paradigm, a morphological box for open data related innovation contests is designed by means of an extensive literature review as well as an empirical investigation of an academic analytics challenge. The resulting artifact guides the design of open data related innovation contests by illustrating the main design elements and their options.

Keywords: Open data, big data, digital innovation, innovation contests, hackathons, datathons

Introduction

Innovation has always significantly contributed to entrepreneurship and business success. In recent years, the traditional closed understanding of innovation has been subject to a rapid change. On the one hand, the open innovation (OI) paradigm shapes the way how innovation processes are designed and how external knowledge contributes to the development of new products and services (Chesbrough, 2003). This trend has been enabled by digitization and internet-based communication facilitating participation and collaborative work. On the other hand, digitization and the internet are also responsible for a massively growing amount of poly-structured data, commonly referred to as big data (Laney, 2001). In particular, the advent of open data all over the world can be considered as a symptom of our increasing data-focused society. According to Open Knowledge International open data is defined as data repositories that are available for everyone and not subject to any restrictions regarding their use, distribution, and modification (http://opendefinition.org/). Along with the emerging opportunities of data analytics, which are fostered by the progress in computing power and new technologies, open data exhibits manifold opportunities for digital value creation (Manyika et al., 2011). Therefore, organizations increasingly consider open data as a valuable resource for innovation and as a means to generate competitive advantages by the use of data analytics (Kiron & Ferguson, 2012). However, although there is broad agreement about such benefits, current research lacks of a theoretical understanding and empirical validation how to enable or trigger innovation by the use of open data (Jetzek, Avital, & Bjorn-Andersen, 2014) and data analytics (Duan & Cao, 2015).

The change towards a mindset for collaboration and data driven innovation is reflected among others by the fact that meanwhile well-established OI methods such as innovation contests or innovation workshops are applied in this context. Organizations have started to provide data in such settings to encourage external stakeholders to participate by improving existing services or by developing new ones (Hjalmarsson & Rudmark, 2012). In particular, open data represents a valuable resource in this context, since it is available free of charge and in data formats (e.g. csv or xml) that can be easily further processed. Our overall research

objective in this context is to reach a better understanding of open data related innovation contests and of the role of data analytics in such contests to derive value from open data. The concrete research question that we aim to answer in the paper at hand can be formulated as follows: "How can organizations be supported in the design of open data related innovation contests?" We consider a morphological box as an appropriate artifact to answer this question as it can serve as a starting point and guide organizations through the design of open data related innovation contests by providing an overview of the main design elements and options. The morphological box will be built by combining the results of a morphological analysis of previous work on related research streams and an empirical analysis of an academic analytics challenge.

The remainder of the paper is organized as follow: First, we present the theoretical underpinnings and the research method. Following the design science research paradigm, we design subsequently the morphological box for open data related innovation contests. Due to the research in progress status we briefly sketch a preliminary evaluation. Finally, we discuss limitations of the paper at hand and our future work.

Theoretical Underpinning

Absorptive Capacity and Open Data Related Innovation Contests

For our research, we draw back on the well-established concept of absorptive capacity as introduced by Cohen & Levinthal (1990). Absorptive capacity can be defined as "the ability of a firm to recognize the value of new, external information, assimilate it, and apply it to commercial ends" (Cohen & Levinthal, 1990, p. 128). Further research has unbundled absorptive capacity in potential and realized absorptive capacity (Zahra & George, 2002) as well as in exploratory, transformative, and exploitative learning absorptive capacity (Lane, Koka, & Pathak, 2006). As highlighted by various researchers, absorptive capacity is critical for successful R&D and innovation.

According to von Hippel (2005), companies can improve the innovativeness and disruptiveness of new products and services by the integration of customers in the development process. Furthermore, Chesbroughs' OI approach delineates an influential mind-set for opening innovation processes in both directions – for the exploration of external knowledge as well as for the exploitation of internal knowledge outward (Dahlander & Gann, 2010).

External knowledge is not only available via stakeholders, it can also be gained from other resources. The emergence of open data, increasingly promoted by governments (Zuiderwijk & Janssen, 2014), results in a large pool of information resources, free of charge and available for everyone. According to McKinsey Global Institute open data holds great potential for innovation and value creation in many industrial sectors (Manyika et al., 2013). Furthermore, the European Commission designated open data as a key driver for promoting governmental transparency (European Commission, 2011).

We argue that the ability of an organization to innovate on open data is related to its absorptive capacity. Due to the emerging phenomenon of open data the organizational ability to explore such data, transform it, and exploit it for developing new products and services is essential from a competition perspective. Combining open data with OI methods gains growing attention in research and practice, since the application of OI has been recognized as a promising means for deriving value from open data (Hjalmarsson, Johannesson, Juell-Skielse, & Rudmark, 2014). Methods for participation and collaboration in OI include, but are not limited to innovation communities, marketplaces, toolkits, contests, and specific technologies (Möslein & Bansemir, 2011). Innovation contests (and some forms of innovation workshops; cf. the subsequent subsection about hackathons and datathons) constitute common OI methods for innovating on open data (cf. Ayele, Juell-Skielse, Hjalmarsson, & Johannesson, 2015; Hjalmarsson et al., 2014; Juell-Skielse, Hjalmarsson, Johannesson, & Rudmark, 2014; Zuiderwijk & Janssen, 2014). We also consider innovation contests as appropriate as they are typically organized in an online setting and therefore can reach a broad audience without limitations due to location or time. In addition, data is anyway provided online in most cases. Nevertheless, other OI methods might also be applied for innovating on open data.

Data Analytics for Innovation

Data analytics is required to transform data into innovation. Considering the role of data analytics for innovation, several perspectives can be identified. Analytics is being used to monitor innovation performance in terms of input, process, and outcome measures (Erkens, Wosch, Piller, & Lüttgens, 2014). Therefore, key performance indicators (KPI) are defined, measured, and arranged in form of dashboards. From this perspective, the overall objectives of analytics are to provide decision support and managerial information for the management, to gain a better understanding of innovation, and to justify decisions in retrospect. For a comprehensive overview of innovation management measures we refer to (Adams, Bessant, & Phelps, 2006). According to Davenport (2013) this role of analytics can be assigned to the "era of business intelligence or, what he calls "analytics 1.0". Analytics focuses then on organizational internal and structured data, usually stored in a data warehouse.

With the advent of big data and the related methods of analytics, such as text analytics, web analytics, and network analytics (cf. H. Chen, Chiang, & Storey, 2012) the traditional role of data analytics has changed. In the era of "analytics 2.0" organizational analytics was no longer limited to internal data but included external data sources from the internet such as open data (Thomas H. Davenport, 2013). To handle the vast amount of data in real-time, new technologies like NoSQL and In-Memory databases were developed (Chen & Zhang, 2014). Building on the success of pioneers from Silicon Valley, foremost Google, Facebook, and Amazon, companies from other industrial sectors recognized the trend towards analytics and created data enriched offerings. This stage is referred to as the current period of "analytics 3.0" by Davenport (2013). The new facilities enable a more active role of analytics for innovation. Instead of a purely descriptive innovation performance measurement, analytics is applied within innovation processes to gain insights about customer needs, open up new business opportunities, and become part of innovative solutions themselves (e.g. in recommendation systems or search algorithms) (H. Chen et al., 2012).

Besides these two perspectives, there is a third option of combining the fields of innovation, analytics, and open/big data. Increasingly, analytics technologies are used to innovate on data, i.e. open/big data is used as a resource for the innovation process. In the paper at hand we focus on this perspective.

Research Method

Design Science Research and Morphological Analysis

Since open data related innovations contests are a fairly new phenomenon, organizations need guidance how to design such contests and how to innovate on open data. Therefore, a morphological box is particularly suitable for demonstrating the solution space and the design elements for open data related innovation contests. In order to develop such an artifact we follow the design science research (DSR) process as introduced by Peffers et al. (2007). DSR is in particular suitable for our problem as it specifically addresses the construction of socio-technical models for the IS domain (Gregor & Hevner, 2013). The DSR approach is also often used to design artifacts in an emerging research field – like it is the case in our context. In accordance with the first step in the DSR process, the benefits of open data related innovation contests and the lack of research and empirical investigation in this field have been discussed in the introduction.

Realizing the next major DSR process step, we apply the general morphological analysis (GMA) (Ritchey, 2011) for the design of the morphological box. GMA is an established method for structuring complex socio-technical problems and derive solutions in a systematic way. Zwicky (1969) provides a process model with five steps for GMA: (1) Identify a problem, (2) define all possible dimensions, which affect the solution for the problem, (3) design a morphological box to specify all characteristic attributes per dimension, (4) analyze the resulting combinations of characteristic attributes, and (5) pick the most suitable solution to solve your problem. We aim at designing the morphological box as a generic and reusable artifact and not at solving a concrete problem (for which the morphological box is used). Therefore, we focus on the GMA steps (2) and (3). In order to identify the design elements (dimensions) and attributes, we mainly build on two sources: the insights from previous literature and the results of an empirical analysis of an academic analytics innovation contest.

Since this is a research in progress the subsequent demonstration and evaluation steps of the DSR process are only briefly sketched in the paper at hand.

Data Collection and Empirical Analysis

In order to get insights about real-world open data related innovation contests we analyzed the Teradata Analytics challenges, organized by the Teradata University Network (TUN). TUN is a web-based portal for faculty and students in big data & analytics, business intelligence, data warehousing, and database management. The network is led by industry experts and faculty from various universities who provide and share content. Since 2014 TUN runs annually an innovation contest, the so-called Analytics Challenge. In this contest student teams (from college or university undergraduate and graduate students) can submit the results of their business analytics research or application cases. Student projects can range from business analytics or marketing analytics to big data and data science. In most cases the students identify and analyze open data. Therefore the competition combines features of hackathons as well as of datathons. A selection committee evaluates the submissions, consisting of an extended abstract and a draft visualization. These materials describe the core elements of the research, including the problem being solved, its significance, the approach adopted, and some key results.

We analyzed a total of 58 submissions from the challenges in 2014, 2015, and 2016. Most submissions were handed in from US universities, two from Singapur and one from Canada. The analysis had two major objectives: on the one hand, to evaluate the dimensions and attributes of the morphological box that we could identify before by the literature review; on the other hand, to potentially identify additional dimensions or attributes that we could not derive by literature. For the analysis two researchers independently hand-coded all submissions based on a criteria catalog. Afterwards, not only the very few different codings were discussed, but especially we identified additional dimensions that exhibit different attributes across the submissions. We consider some of those dimensions as relevant for the morphological box for open data related innovation contests and therefore added them to the artifact.

The resulting dimensions from the literature review as well as from the empirical analysis will be presented in the following.

Morphological Analysis

We conducted a literature review on innovation contests in general as well as on data-related contests, namely hackathons and datathons. All dimensions and attributes of those dimensions that we could identify by means of this literature analysis, are highlighted in the following by *italic font*. Afterwards we present the results of the empirical analysis of the Teradata Analytics challenges.

Innovation Contests

Innovation contests are competitions about specific topics in which interested participants are invited to submit their contributions in form of ideas, concepts, or solutions to win a monetary or non-monetary reward. Different approaches deal in literature with this phenomenon. Piller & Walcher (2006) focus on user integration via toolkits for idea competitions in the manufacturing industry, while Hjalmarsson and Rudmark (2012), Hjalmarsson et al. (2014) and Juell-Skielse (2014) investigate the design of digital innovation contests and the role of innovation contests for the development of open data services. Bullinger and Moeslein (2010) present various design elements for innovation contests, which fit due their generic nature also very well for our context of open data related innovation contests. Therefore, we decided to integrate them as dimensions in the morphological box. They are presented in detail in the following paragraph.

The competitions can take place in an *online* or *offline* environment as well as in a *combination of both (mixed) (*dimension *media)*. Online innovation contests are organized or at least promoted on virtual platforms, such as internet communities or social networks. Thereby, such competitions benefit from the proliferation of internet-based communication, which allows people to participate irrespectively of time and place. This change towards Web 2.0 applications results in a more efficient communication between the participants and thus, has a positive effect on innovation success (Füller, Bartl, Ernst, & Mühlbacher, 2006). In order to benefit from this trend, innovation contests can also include *functionalities of an online community (*attributes *given/non given)* (Bullinger, Neyer, Rass, & Moeslein, 2010). Furthermore, innovation contests can be organized (dimension *organizer*) from *companies*, from the *public*, or *non-profit* sector as well as from *individuals*. The *specificity* of the assigned task can vary in a range from *open*

over *defined* to *specific*. The contests can have various objectives and are suitable for different stages of the innovation process, such as idea generation, conceptualization, or prototyping. Hence, the *degree of elaboration* varies (attributes *idea/sketch/concept/prototype/solution/evolving*). Innovation contests target (dimension *target group*) at a *specific* group of experts in a field or address the crowd in general (attribute *unspecified*) and the participants can work *individually* as well as in *teams* (dimension *participation)*. Innovation contests take place in a range from a *very short* (hours or a couple of days), a *short*, a *long* to a *very long* (months or ongoing) *contest period*. To incite the participants contest organizers can provide *monetary*, *non-monetary, or mixed rewards*. The *evaluation* of the submissions will be conducted by means of a *jury decision*, a *peer review*, a *self assessment,* or *mixed*.

Hackathons and Datathons

Innovation workshops have their intellectual roots in the literature on lead user innovation (Herstatt & von Hippel, 1992; von Hippel, 1986). In general, innovation workshops provide a framework in which participants collaborate on challenges or problems in an interactive and structured way. They aim at the integration of engaged and front running users in the development process of new products and services to bypass intermediaries such as retailers or market researchers (Nambisan, 2003). Participants in such workshops consist mostly of experts or so called lead users who express their needs and desires about a product or service at an early stage and anticipate the future needs of the mass market (von Hippel, 1986).

With the advent of the internet new types of innovation workshops have been established since the late 1990s. In 1999 a group of OpenBSD (a linux derivate) developers organized a computer programming event in Calgary, designated as a so-called hackathon. Since then, such meetings have become increasingly popular and are organized by governments or private organizations. Hackathons are events, at which the participants work together on a programming task or another software project over a short period of time (Briscoe & Mulligan, 2014). In general, hackathons are built on the participatory efforts of interdisciplinary teams. However, they are often organized as innovation contests with rewards (Johnson & Robinson, 2014). Briscoe and Mulligan (2014) distinguish between *tech-centric* and *focus-centric* hackathons (dimension *application area)*. Tech-centric hackathons can encompass programming tasks regarding single applications, application types (e.g. web applications), or specific technologies (e.g. programming language), while focus-centric hackathons deal with social, demographic, or business issues. To cover all shapes of such contests we add the attribute *mixed* to this dimension in the morphological box.

Recently, a new phenomenon can be observed, which had gained less attention in research before. So-called datathons transfer the hackathon concept to challenges with regard to data analytics (Aboab et al., 2016). The range of tasks can be diverse, from data preprocessing and cleansing to data mining and data visualization (Anslow, Brosz, Maurer, & Boyes, 2016). We cover this aspect by the dimensions *data value chain* and *analytics technologies* which will be introduced in the following subsection. Applying analytics requires a variety of capabilities: besides *analytics* know-how also statistical, mathematical, and *programming* skills (T. H. Davenport & Patil, 2012) (dimension *skill focus*). Datathon participants should be assembled in *interdisciplinary* teams (Aboab et al., 2016), however can also be part of *monodisciplinary* teams (dimension *team composition*). Besides these characteristics, the underlying data sets play an important role, since they are the foundation of any innovative effort. Datathons are often conducted on the basis of open data repositories. The datathon organizer can *provide* a dataset or let the participants collect the data by themselves (*self-organized*) or both options are combined (*mixed*) (dimension *data provision*).

Analysis Results of the Teradata Analytics Challenges

When coding the submissions of the Teradata Analytics Challenge we could identify additional criteria that have (mostly) been named in previous literature about data driven innovation and data value chains: Vanauer, Bohle, & Hellingrath (2015) distinguish two fundamental ways how the ideation stage (dimension *ideation approach*) in a data driven innovation process can be guided: the *business first perspective* starts with business requirements and aims at meeting those business questions by the means of available (big) data and technologies. The *data first perspective* emphasizes the enabling role of data and analytics. Therefore the ideation process is driven and inspired by available data and technologies and is open for new business models or use cases. We could find both perspectives applied in the students´ submissions. Some teams formulated the business questions first and then looked for appropriate data (and/or ways to answer

the questions by provided data); other teams investigated available (or self-selected) data and came by that to new ideas how to gain insights from the data.

Another relevant aspect refers to the key activities in *data value chains*. Compiling previous work from (Curry, 2016), (Hartmann, Zaki, Feldmann, & Neely, 2014), and (Miller & Mork, 2013) we have identified the following key activities which we could also find in various combinations in the students submissions: *data generation, data acquisition, data processing, data aggregation, analytics, and visualization*. As most open data related innovation contests include some kind of analytics we have added two criteria to the morphological box which describe such analytics in more detail. The established categorization of analytics (dimension *analytics perspective*) into *descriptive, predictive, and prescriptive analytics* (Chen et al., 2012) is applicable to the submissions as well as Chen et al.´s (2012) *analytics technologies* which we have adopted slightly to our context and which are constituted in the morphological box by the following attributes: *data analytics, text analytics, network analytics, and streaming analytics*.

To capture the variety of data collection options that we could see in the submissions we finally added the following dimensions and attributes: *number of data sources (one or few/some/many), data source type (open data/own data/company data) and data integration, if several data sources (no data integration/integrated*).

Morphological Box for Open Data Related Innovation Contests

Table 1 summarizes the findings of the literature review and of the empirical analysis of the Teradata Analytics challenges.

Evaluation

Although a comprehensive evaluation of the morphological box is subject to future work due to the research in progress status, we could already test it to a certain extend when analyzing the Teradata Analytics Challenge submissions. As the challenge is a concrete innovation contest the attributes of the first part of the morphological box (related to innovation contest settings) didn't vary within the submissions. However, for the second and third part of the artifact we could observe most attributes in the submissions.

We aim to demonstrate and evaluate our artifact within the research project CODIFeY – Community based service innovation for e-mobility (cf. Dinter, Kollwitz, Möslein, & Roth, 2016) following an action design research approach (Sein, Henfridsson, Rossi, & Lindgren, 2011).

Limitations and Future Research

In this research in progress paper we have designed a morphological box for open data related innovation contests as a first step for a better understanding of this increasingly relevant phenomenon. We have combined the results from a literature review, representing the state of the art in research, and the findings from the analysis of a series of academic open data related innovation contests. This morphological box can serve as a starting point for more detailed research.

Our future work aims also at overcoming the limitations that the current research in progress has. We plan to extend our analysis of the Teradata Analytics Challenge by conducting interviews with the students and with their supervisors. We expect to get deeper insights about the innovation process itself, like how the students have identified open data sources, how they came to business questions, etc. The empirical analysis needs also to be applied to open data related contests in other settings, in particular in non-academic settings. In addition, we plan to analyze and interpret the patterns that are formed by contests to get a better understanding of typical real-world situations for open data related innovation. The resulting insights can serve as a starting point for further research, such as the design of a methodology for open data related innovation.

Source	Dimension	Attributes					
Literature on innovation contests (Bullinger and Möslein 2010)	Media	Online		Mixed		Offline	
	Organizer	Company	Public		Non-profit		Individual
	Task specificity	Low/Open		Defined		High/Specific	
	Degree of elaboration	Idea	Sketch	Concept	Prototype	Solution	Evolving
	Target group	Specified			Unspecified		
	Participation as	Individual		Team		Both	
	Contest period	Very short	Short		Long		Very long
	Reward	Monetary		Non-monetary		Mixed	
	Community functionality	Given			Not given		
	Evaluation	Jury	Peer review		Self-assessment		Mixed
Literature on hackathons / datathons	Application area	Tech-centric		Focus-centric		Mixed	
	Skill focus	Programming		Analytics		Mixed	
	Team composition	Monodisciplinary			Interdisciplinary		
	Data provision	Provided		Self-organized		Mixed	
Evaluation of the Teradata Analytics challenge	Number of data sources	One or few		Some		Many	
	Kind of data source	Open data		Own survey		Company data	
	Data integration (if several data sources)	No data integration			Integrated		
	Ideation approach	Data first			Business first		
	Data value chain	Data generation	Data acquisition	Data processing	Data aggregation	Analytics	Visualization
	Analytics perspective	Descriptive		Predictive		Prescriptive	
	Analytics technologies	Data analytics	Text analytics		Network analytics		Streaming analytics

Table 1: Morphological box for open data related innovation contests

References

Aboab, J., Celi, L. A., Charlton, P., Feng, M., Ghassemi, M., Marshall, D. C., Mayaud, L., Naumann, T., Mccague, N., Paik, K. E., Pollard, T. J., Resche-rigon, M., Salciccioli, J. D., and Stone, D. J. 2016. "A 'datathon' model to support cross-disciplinary collaboration," Science Translational Medicine (8:333), pp. 1–5.

Adams, R., Bessant, J., and Phelps, R. 2006. "Innovation management measurement: A review," International Journal of Management Reviews (8:1), pp. 21–47.

Anslow, C., Brosz, J., Maurer, F., and Boyes, M. 2016. "Datathons: An Experience Report of Data Hackathons for Data Science Education," in Proceedings of the 47th ACM Technical Symposium on Computer Science Education (SIGCSE), Memphis, USA, pp. 615–620.

Ayele, W., Juell-Skielse, G., Hjalmarsson, A., and Johannesson, P. 2015. "Evaluating Open Data Innovation : A Measurment Model for Digital Innovation Contests," in Proceedings of the 19th Pacific Asia Conference on Information Systems (PACIS), Singapore, pp. 1–15.

Briscoe, G., and Mulligan, C. 2014. "Digital Innovation: The Hackathon Phenomenon," CreativeWorks London Hub (available at http://www.creativeworkslondon.org.uk/publications/working-papers-research/).

Bullinger, A. C., and Möslein, K. M. 2010. "Innovation Contests – Where are we ?," in Proceedings of the 16th Americas Conference on Information Systems (AMCIS), Lima, paper 28.

Bullinger, A. C., Neyer, A.-K., Rass, M., and Moeslein, K. M. 2010. "Community-Based Innovation Contests: Where Competition Meets Cooperation," Creativity and Innovation Management (19:3), pp. 290–303.

Chen, C. L. P., and Zhang, C.-Y. 2014. "Data-intensive applications, challenges, techniques and technologies: A survey on Big Data," Information Sciences (275), pp. 314–347.

Chen, H., Chiang, R. H. L., and Storey, V. C. 2012. "Business Intelligence and Analytics: From Big Data To Big Impact," MIS Quarterly (36:4), pp. 1165–1188.

Chesbrough, H. 2003. Open Innovation The New Imperative for Creating and Profiting from Technology, Boston: Harvard Business School Press.

Cohen, W. M., and Levinthal, D. A. 1990. "Absorptive Capacity: A New Perspective on Learning and Innovation," Administrative Science Quarterly (35:1), pp. 128–152.

Curry, E. 2016. "The Big Data Value Chain: Definitions, Concepts, and Theoretical Approaches," in New Horizons for a Data-Driven Economy. J. M. Cavanillas, E. Curry, and W. Wahlster (eds.), Berlin: Springer, pp. 29–37.

Dahlander, L., and Gann, D. M. 2010. "How open is innovation?," Research Policy (39:6), pp. 699–709.

Davenport, T. H. 2013. "Analytics 3.0," Harvard Business Review (12), pp. 65–72 (available at https://hbr.org/2013/12/analytics-30).

Davenport, T. H., and Patil, D. J. 2012. "Data Scientist: The Sexiest Job of the 21st Century," Harvard business review, pp. 70–76 (available at http://128.255.244.58/strategic/articles/data_scientist-the_sexiest_job_of_the_21st_century.pdf).

Dinter, B., Kollwitz, C., Möslein, K., and Roth, A. 2016. "Combining Open Innovation and Knowledge Management for a Communities of Practice - An Analytics Driven Approach," in Proceedings of the 22nd Americas Conference on Information Systems (AMCIS), San Diego, paper 30.

Duan, Y., and Cao, G. 2015. "Understanding the Impact of Business Analytics on Innovation," in Proceedings of the 23th European Conference on Information Systems (ECIS), paper 40.

Erkens, M., Wosch, S., Piller, F., and Lüttgens, D. 2014. "Measuring open innovation : A toolkit for successful innovation teams," Performance (6:2), pp. 12–23.

European Commission. 2011. "Open data : An engine for innovation, growth and transparent governance," (available at http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=COM:2011:0882:FIN:EN:PDF).

Füller, J., Bartl, M., Ernst, H., and Mühlbacher, H. 2006. "Community based innovation: How to integrate members of virtual communities into new product development," Electronic Commerce Research (6:1), pp. 57–73.

Gregor, S., and Hevner, A. R. 2013. "Positioning and Presenting Design Science Research for Maximum Impact," MIS Quarterly (37:2), pp. 337–355.

Herstatt, C., and von Hippel, E. A. 1992. "From experience: Developing new product concepts via the lead user method: A case study in a 'low tech' field," Journal of Product Innovation Management (9:3), pp. 213–221.

von Hippel, E. 1986. "Lead Users: A Source of Novel Product Concepts," Management Science (32:7), pp. 791–805.

von Hippel, E. 2005. Democratizing Innovation, Cambridge, USA: MIT Press.

Hartmann, P. M., Zaki, M., Feldmann, N., and Neely, A. 2014. "Big Data for Big Business?," Cambridge Service Alliance Blog (available at http://cambridgeservicealliance.blogspot.co.uk/2014/04/big-data-for-big-business_3.html).

Hjalmarsson, A., Johannesson, P., Juell-Skielse, G., and Rudmark, D. 2014. "Beyond Innovation Contests: A Framework of Barriers to Open Innovation of Digital Services," in Proceedings of the 22th European Conference on Information Systems (ECIS), Tel Aviv, pp. 1–15.

Hjalmarsson, A., and Rudmark, D. 2012. "Designing Digital Innovation Contests," in Proceedings of the 7th International Conference on Design Science Research in Information Systems (DESRIST), Las Vegas, pp. 9–27.

Jetzek, T., Avital, M., and Bjorn-Andersen, N. 2014. "Data-Driven Innovation through Open Government Data," Journal of theoretical and applied electronic commerce research (9:2), pp. 100–120.

Johnson, P., and Robinson, P. 2014. "Civic Hackathons: Innovation, procurement, or civic engagement?," Review of Policy Research (31:4), pp. 349–357.

Juell-Skielse, G., Hjalmarsson, A., Johannesson, P., and Rudmark, D. 2014. "Is the Public Motivated to Engage in Open Data Innovation?," in International IFIP Electronic Government (EGOV), Dublin, pp. 277–288.

Kiron, D., and Ferguson, R. B. 2012. "Innovating With Analytics," MIT Sloan Management Review (54:1), pp. 1–8.

Lane, P. J., Koka, B. R., and Pathak, S. 2006. "The Reification of Absorptive Capacity: A Critical Review and Rejuvenation of the Construct," Academy of Management Review (31:4), pp. 833–863.

Laney, D. 2001. "3D Data Management: Controlling Data Volume, Velocity, and Variety.," META Group (Gartner) (Vol. 949) (available at blogs.gartner.com/doug-laney/files/2012/01/ad949-3D-Data-Management-Controlling-Data-Volume-Velocity-and-Variety.pdf).

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., and Byers, A. H. 2011. "Big data: The next frontier for innovation, competition, and productivity," McKinsey Global Institute (available at http://www.mckinsey.com/business-functions/business-technology/our-insights/big-data-the-next-frontier-for-innovation).

Manyika, J., Chui, M., Groves, P., Farrell, D., Kuiken, S. Van, and Doshi, E. A. 2013. "Open data: Unlocking innovation and performance with liquid information," (available at http://www.mckinsey.com/business-functions/business-technology/our-insights/open-data-unlocking-innovation-and-performance-with-liquid-information).

Miller, H. G., and Mork, P. 2013. "From data to decisions: A value chain for big data," IT Professional (15:1), pp. 57–59.

Möslein, K. M., and Bansemir, B. 2011. "Strategies and communications for innovations: An integrative management view for companies and networks," in Strategies and Communications for Innovations: An Integrative Management View for Companies and Networks. M. Hülsmann and N. Pfeffermann (eds.), Berlin: Springer, pp. 11–23.

Nambisan, S. 2003. "Information systems as a reference discipline for new product development," MIS Quarterly (27:1), pp. 1–18.

Peffers, K., Tuunanen, T., Rothenberger, M. A., and Chatterjee, S. 2007. "A Design Science Research Methodology for Information Systems Research," Journal of Management Information Systems (24:3), pp. 45–77.

Piller, F. T., and Walcher, D. 2006. "Toolkits for idea competitions: A novel method to integrate users in new product development," R & D Management (36:3), pp. 307–318.

Ritchey, T. 2011. Wicked problems–social messes: Decision support modelling with morphological analysis, Berlin: Springer.

Sein, M. K., Henfridsson, O., Rossi, M., and Lindgren, R. 2011. "Action Design Research," MIS Quarterly (35:1), pp. 37–56.

Vanauer, M., Bohle, C., and Hellingrath, B. 2015. "Guiding the introduction of big data in organizations: A methodology with business- and data-driven ideation and enterprise architecture management-based implementation," in Proceedings of the 48th Hawaii International Conference on System Sciences (HICSS), Kauai, pp. 908–917.

Zahra, S. A., and George, G. 2002. "Absorptive Capacity: A Review, Reconceptualization, and Extension," Academy of Management Review (27:2), pp. 185–203.

Zuiderwijk, A., and Janssen, M. 2014. "Open data policies, their implementation and impact: A framework for comparison," Government Information Quarterly (31:1), pp. 17–29.

Zwicky, F. 1969. Discovery, invention, research through the morphological approach, New York: MacMillian.