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Towards the Development of a Typology of Big Data Analytics in Innovation Ecosystems

Research-in-Progress

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Abstract

The digital transformation of society and economy leads to fundamental changes in the planning and execution of innovation processes in organizations. Possibilities and application scenarios of digital, data-driven innovation are frequently discussed in academia and in industry, but a comprehensive and systematic examination of the various types and roles of big data analytics technologies in innovation ecosystems is currently missing. Organizations need support in identifying and implementing the new opportunities of big data analytics to generate value through innovation. Starting from the theoretical perspective of service-dominant logic, we present a three-dimensional conceptual framework with associated characteristics that can be used to derive different archetypes of big data analytics in innovation ecosystems. The findings will be further developed as part of a qualitative case study in the field of electromobility in Germany.

Keywords

Innovation, Big Data Analytics, Service-Dominant Logic, Typology.

Introduction

In the course of the progressing digitalization, emerging information technologies and omnipresent large amounts of poly-structured data are radically changing the nature of organizational innovation processes as well as their outcomes (Yoo et al. 2010). This trend manifests itself in the fact that data and corresponding analytics techniques (in the following referred to as big data analytics) are increasingly considered as valuable resources for decision support in innovation management, the development of innovative products/services (Demirkan et al. 2015) and/or as a foundation of new business models (Hartmann et al. 2016). Although the literature refers to potentials and success stories of so-called data-driven innovation (Cavanillas et al. 2016) and first studies explore the effects of big data analytics on organizational innovation processes (Vanauer et al. 2015), a more in-depth theoretical understanding of roles and functions of information technologies and big data analytics for innovation is required. In addition, the effects on management and the design of innovation processes and ecosystems have to be investigated (Nambisan 2013). In particular, there is a need for studies, which examine the interaction between the use of technology in innovation ecosystems and technology as a result of innovation in more detail (Nambisan et al. 2017) and thereby focus on the duality of technologies (Orlikowski 1992). The research question of this RIP paper is derived from these research demands: *How can the various tasks and roles that big data analytics can assume for innovation in companies be systematized?*

In order to answer the research question, a typology will be developed from the theoretical perspective of the service-dominant logic (SDL) (Vargo and Lusch 2004). The SDL serves as a theoretical foundation, as it enables a detailed analysis of innovation mechanisms through a condensed understanding of innovation as a resource-based exchange and integration process between different actors. Based on Arthur's (2009) combinatorial understanding of innovation, we derive a framework from the literature, which will subsequently be applied and demonstrated in the context of a case study in the field of service innovation for electric mobility in Germany. The case study was conducted as part of a multi-year research project and examines the use of analytics technologies in various service innovation scenarios, such as innovation communities and hackathons. The approach combines deductive and inductive research by presenting established knowledge as a framework developed from literature, which is empirically validated and refined. In the Foundations Section, the underlying theoretical perspective of this article and a concise state-of-the-art description of the role of big data analytics in innovation ecosystems are presented. The Section Research Approach describes the applied research method and situates the paper in the CODIFeY research project, while in the subsequent Section a preliminary framework is developed on which our further work will be based on. Finally, the next steps in the research process are outlined in the last Section.

Foundations

The Role of Technology for Innovation Ecosystems

The SDL is frequently used to conceptualize innovation ecosystems, in particular in the field of service innovation (Lusch and Nambisan 2015). We define innovation ecosystems according to Autio and Thomas (2014) as network of interconnected actors (e.g. companies or customers) arranged around an organization or platform focusing on the creation of value through innovation. The different actors in innovation ecosystems integrate and combine different types of tangible or intangible resources. For instance, they combine raw materials (tangible) with their ability to process them (intangible) into novel products.

The theory of SDL provides an expanded view of the role and importance of technology in innovation ecosystems. On the one hand, technology is regarded as a central success factor and driving engine for successful innovation and on the other hand, the development of new technology is often the goal of innovative efforts (Akaka and Vargo 2013). Orlikowski's "Structurational Model of Technology" (Orlikowski 1992) underlines this duality of technology as (1) the result of physical action in the sense of innovative activity and (2) technology as a means or medium for innovation, which can be interpreted differently depending on the social context and the actors involved. From an SDL point of view, the role as a result of an activity corresponds to that of an operand resource, while its role as a means of innovation tends to correspond to that of an operant resource (Vargo and Akaka 2012). The distinction between operand and operant resources is based on the "Resource-Advantage Theory" according to Hunt (2000) and adapted by SDL. Operand resources are resources that are acted upon in order to achieve an effect. On the other hand, operant resources, when applied to other resources, generate an effect (Constantin and Lusch 1994). Over time, it has become established that resources can be used both operand and operant regardless of their original nature (Lusch and Nambisan 2015).

According to Arthur (2009), technology can be understood as (1) a process of satisfying needs, (2) an accumulation of practices and procedures, and (3) a sum of all things or procedures ever developed by humans that are available to a civilization. Arthur describes the development of technologies as a process of recombination of (operant) resources. Thus, by combining technology with other resources, new technology emerges. Novel information technology has a crucial role in innovation because it can be used as infrastructure (e.g. for communication and interaction in the innovation process) (Lusch and Nambisan 2015). The task of information technology as an operant resource is to stimulate and trigger innovation (Nambisan 2013). The increasing digitalization and dissemination of knowledge and information create new possibilities to integrate resources. This can affect both the process dimension (development) and the outcome dimension (product/service) (Nambisan 2013).

Big Data Analytics in Innovation Ecosystems

The continuous development of big data analytics technologies requires an increasing strategic importance of data as a key resource in global competition. As a result, there is a growing interest in making them available for innovation both in academia (Cavanillas et al. 2016; Demirkan et al. 2015) and in industry (Manyika et al. 2011). In general, the use of data for innovation activities in companies is also referred to as data-driven innovation (Stone and Wang 2014). As already mentioned in the introduction, big data analytics can take on various tasks in innovation ecosystems. Urbinati et al. (2019) differentiate the benefits of big data analytics for innovation from a company's perspective based on different fields of action such as customer needs identification, service design or risk management. Chen et al (2012) as well as Davenport (2013) describe an evolutionary development in three consecutive stages that encompass different characteristics of big data analytics. Starting from a passive and descriptive understanding, which primarily aims at the management and controlling of innovation processes and the collection of key performance indicators, big data analytics increasingly assume an active and complementary role in value creation. As a result, organizations using big data analytics to offer products and services enriched with data or as analytics-as-a-service to place them at the at the core of their portfolio (Delen and Demirkan 2013).

Research Approach

In order to gain a deeper theoretical understanding of new and insufficiently investigated phenomena, Corbin and Strauss (2015) propose to use qualitative research approaches as a means of in-depth and comprehensive research. According to Yin (2018), case studies represent a particularly suitable qualitative, empirical method for investigating phenomena in their depth and under real conditions, thus investigating their limits and possibilities. A single case study with holistic design (Yin 2018) was chosen in the context of this paper. In order to answer the research question, such a single case study seems to be suitable to reduce the complexity of big data analytics in innovation ecosystems and to consider the phenomenon over a long period in a superordinate coherent context (Halinen and Törnroos 2005). The case study was conducted as part of the research project "Community-based Service Innovation for e-Mobility" (CODIFeY) in the years 2014 – 2017, which was funded by the German Federal Ministry of Education and Research. During the research project, various service innovation methods for the development of user-friendly electro mobility services were applied. In particular, CODIFeY focused on three innovation cycles (periodical innovation processes):

- The collection, processing and analysis of user data to support decision-making for the management of an online innovation community (Dinter et al. 2016),
- The support of activities at the beginning of the innovation process by means of various analytics methods (Wehnert et al. 2018) and
- The development of data-driven service innovations in workshops and hackathons using freely available data sets (so-called open data) (Dinter and Kollwitz 2016).

The data collection took place over the entire project with the help of various techniques, including interviews, academic focus groups, participant observation and documentary research. Further research on this topic will combine the empirical findings from the case study with the framework presented in the following section to generate deeper insights into the roles and types of big data analytics in innovation ecosystems.

Towards a Typology of Big Data Analytics in Innovation Ecosystems

Based on the findings from Section 2, this section will present a preliminary version of a framework, which will serve to systematize big data analytics in innovation ecosystems. Thereby, different distinctively dimensions are outlined and described. A summary can be found in Figure 1.

The first dimension is originally based on Nambisan (2013), which distinguishes two dimensions concerning the use of technologies for innovation. The first dimension, *Scope*, addresses the duality of technology, which can be traced back to Orlikowski (1992). Accordingly, technologies determine the innovation process on the one hand, but on the other they can also be an integral part of the innovation result. For example, big data analytics are used to increase efficiency of activities within the innovation process or to provide decision support for innovation management by monitoring the entire process. On the other hand, big data analytics can also be part of an innovative solution, e.g. a recommender system can be part of a digital service, such as a streaming service for media content.

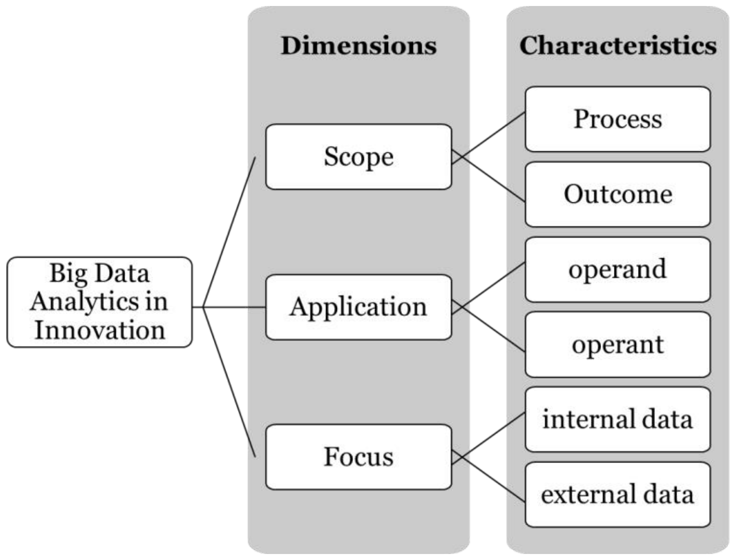

Figure 1. Framework for the Characterization of Big Data Analytics in Innovation Ecosystems

The second dimension, *Application*, contains the SDL distinction between operand and operant technology application. An operand use exists when technologies assume the role of an "enabler" and have minor influence on the innovation process or result. Example are incremental process improvements and/or the embedding of complementary value-added services in existing product and service architectures. An operant application exists when technologies exert a disruptive influence on innovation processes or results and lead to utterly new solutions. In this scenario, the technology triggers new processes and innovation results that would be inconceivable without their existence.

Based on Orlikowski's work, the third dimension, *Focus*, is considered for our framework. This refers to institutional conditions, which influence the interaction of technology and innovation (Orlikowski 1992). One trend that can be observed in this context since the beginning of the 2010s is a shift away from a focus on internal resources towards the integration of external resources. In the area of innovation, this development manifests itself under the term open innovation (Chesbrough 2006) through the integration of stakeholders (e.g., customers or suppliers) in innovation processes, while in the area of big data analytics it is explained by the increasing availability of external data, which is enabled by trends such as social media and open data. Thus, the third dimension of the framework addresses the focus on internal and external data.

Further research

This RIP paper is a first step towards the development of a typology for the use of big data analytics in innovation ecosystems. Based on the combinatorial understanding of innovation and the understanding of technology of Orlikowski (1992), a framework was deduced, which will be further developed by the empirical findings from the CODIFeY case study. In a first step, the three dimensions of the framework will be validated in order to fathom the different combinations of characteristics more precisely with the help of the case study. This will result in a detailed elaboration of different archetypes of big data analytics in innovation ecosystems, which can be described based according the dimensions and characteristics of the framework. On the one hand, these archetypes should help to establish a better understanding of digital and data-driven innovation in organizations and thus contribute to the knowledge base in the areas of innovation management and big data analytics. On the other hand, organizations should be sensitized and enabled to recognize the different possibilities of big data analytics for their own innovation ecosystems.

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