Approaches to the implementation of big data analytics

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Everyone is talking about big data analytics

It seems that there is no area in our everyday lives that is not influenced by big data and big data analytics (BDA). The term big data refers to a high volume, variety, velocity, and veracity of data, while BDA refers to methods and tools for gathering, processing, and analyzing big data (Chen et al. 2012).

Besides the constantly increasing number of individualized applications enabled by the gathering and analysis of big data, BDA also attracts attention from a social-policy perspective. The debate about the downsides of BDA has broadened, especially in the last five years. Many newspapers address stolen or illegal capture of personal data and its unethical use (e.g., Lieber 2017, Tufekci & King 2014), and experts warn about unfair classification of individuals that leads to discrimination (Markus 2015; Newell & Marabelli 2014). The limitations of our decision-making abilities are also frequently cited as problematic, as when political parties use information about individuals to influence their opinions (e.g., Hern 2017). Accordingly, people increasingly see in BDA a threat to privacy, freedom, and democracy, a view that is often accompanied by fear. For example, according to one US survey, more than 45 percent of those who use wearable devices are concerned about the devices' ability to breach their privacy (Mills 2015). Paradoxically, consumers enjoy using mobile apps that provide individualized service, reading individualized newsfeeds, and using wearable devices for self-tracking (IDC 2015).

Despite the potential for negative consequences, many companies use BDA to provide new services that can make our lives easier. As BDA has proliferated and data sources have increased in number and volume, companies seek to leverage the transformational impact of BDA for service innovations (Woerner & Wixom 2015) that benefit customers and create competitive advantages (Skålén et al. 2016). Specifically, service innovation focuses on new ways of creating value for customers by establishing new activities or realigning existing ones to improve service delivery (Orlikowski & Scott 2015). For example, industrial companies like Schindler and the Swiss Federal Railways (SBB) Company see in BDA an enabler for creating smart cities (SBB 2018, Schindler 2017) that will enhance the habitants' quality of life. Car manufacturers like Porsche use BDA to create innovative services in the context of connected cars (Freimark 2014) that provide the consumer with a safer and more efficient driving experience. Similarly, insurance companies like AXA are designing analytics-based services like the AXA drive coach app that make lives safer (Tardy 2015). Consumer goods companies use BDA to adapt their products to individual needs and improve the customer's experience. For example, Whirlpool, the home-appliances manufacturer, put sensors in its products to track how customers use them and combining these data with user-generated content from social media platforms (e.g., product reviews) to offer predictive maintenance services, reducing customers' stress and increasing their products' reliability (Woerner & Wixom 2015).

Against this background, it is clear that BDA should not be associated only with its negative potential but also with the potential to add value for the consumer (Woerner & Wixom 2015). Despite the impression that BDA is in league with the devil, companies can use new approaches to harness its positive potential.

Bringing the scientific and practical perspective together – A guide addressing the challenges of BDA

Data about a company's actual and potential consumers, their environment, and the products they use is extremely valuable to that company. Statements like that of Peter Sondergaard of the Gartner Group that "*information is the oil of the 21st century, and analytics is the combustion engine*" (Goes, 2014, p. iii) and The Economist's observation that "*Data are becoming the new raw material of business*" (2010, as cited in Goes, 2014, p. iii) are well known. McAfee and Brynjolfsson (2012) labeled BDA a "*Management Revolution*" (p. 3).

However, in reality, many companies struggle to capitalize on BDA (Chen et al. 2015). Thus, I explain and provide insights into three fundamental challenges companies face when implementing BDA—failure to understand the term "BDA," lack of knowledge about the potential for its use, and missing information about the required practices and process for implementing it.

The insights are based on my experiences during a practice-oriented research project I started in 2014. I spoke to several experts in the BDA field and made several observations about its application to service innovation. I also held several workshops with executives of companies in Switzerland and Germany who were exploring new application areas for BDA. I also referred to the scientific literature to extend the practical viewpoints.

This paper contributes to practice-oriented BDA (e.g., McAfee & Brynjolfsson, 2012) and provides a novel perspective on how BDA influences companies' business success. Specifically, it contributes to the idea of Analytics 3.0 introduced by Davenport (2013) by providing companies with insights into how BDA can empower customer service processes.

Challenges regarding BDA – What is it? Why is it valuable? How to implement it?

What is BDA?

In many companies I observed a lack of understanding of the term "BDA." Some companies' employees label BDA data analytics because they do not see many differences between BDA and the conventional way of analyzing data. As a result, these companies may focus solely on improving their business intelligence initiatives or fail to consider the specific requirements of BDA, and they wander about making slight improvements that focus primarily on their existing reporting landscapes. Failing to work at conceptualizing the term, they do not extend their mind sets to consider new possibilities. Companies' employees that have a more advanced understanding of BDA use, for example, the term "advanced analytics" to highlight the new opportunities BDA provides. However, the term "advanced analytics" can also be interpreted in a variety of ways, so many companies struggle to agree internally on a common understanding of what is "in scope" and what it "out of scope" when they talk about "advanced analytics."

These observations are in line with the scientific literature's ongoing discussion about how to define big data and BDA. Amott and Pervan (2014) stated that "*there is no accepted definition of big data*" (p. 271), while Baesens et al. (2016) differentiated BDA from business intelligence when they introduced the term "business analytics" as "*encompass[ing] all aspects of the data process to facilitate predictive and/or causal inference-based business decision making*" (p. 808).

Why is BDA valuable?

How BDA contributes to the overall company's success remains unclear for many executives. Based on my experiences, there is scarce knowledge about BDA's potential in the context of service innovation, and executives struggle to derive a strategic approach to implementing BDA. These observations are comparable to the assumptions made by several researchers. For example, Chen et al. (2015, p. 5) stated, "*a majority of companies have still not begun to engage in the practice of capitalizing on big data*" and

Lavalle et al. (2011, p. 23) explained that "*the leading obstacle to widespread analytics adoption is lack of understanding of how to use analytics to improve the business*."

How to implement BDA

Many firms do not understand how to implement BDA, so they do not use a systematic approach in implementing their BDA-related initiatives. Some companies follow a bottom-up approach and start by investing in technological solutions like Data Lake. These companies invest considerable money without having a concrete idea about promising ways to use the technology, how to define promising use cases, and how to link their BDA initiative to the company's overall objectives. I recognized that firms lack a systematic approach to the required practices and processes and the tools and techniques that provide guidance in problem-solving when implementing BDA. These observations are in line with the scientific literature, such as the work of LaValle et al. (2011, p. 21), who stated that "*the biggest challenge in adopting analytics are managerial and cultural*."

Three approaches to the implementation of BDA

BDA – An explorative approach to data analytics

BDA describes a new stage of business intelligence (Chen et al. 2012). The ongoing development of business intelligence and analytics solutions occurs primarily because of the unprecedented amount of data generated by an increasing number of sources and the widening possibilities for gathering, processing, and analyzing them (Chen et al. 2012). To explain BDA, I decompose the term into its two parts: big data and BDA.

When we use e-commerce, social media platforms, and digitized objects like smartphones and wearables, we leave a digital trace of data about our behavior and thoughts that is often referred to as digital trace data (Müller et al. 2016; Newell & Marabelli 2015). In addition, many companies generate a vast amount of data by, for example, using sensors in their products or digitalizing their business processes (e.g., paper-less customer interaction). These kinds of internal and external data can be encompassed under the umbrella term "big data" (Debortoli et al. 2014; Newell & Marabelli 2014). Big data has specific characteristics. For example, web-based and sensor data are both generated in high volumes (large-scale data), at high velocity (high-speed data), in wide variety (e.g., text-based data and numerical data), and with high veracity (e.g., sensor data) (Debortoli et al. 2014). These "four Vs" are well known, but there is an ongoing debate about which is the most important (Goes 2014).

The volume of data collected is central to big data's potential. Practitioners and scientists (e.g., Clarke 2016) have found that the unprecedented volume of data now available creates new possibilities for data analysis that provide, for example, new opportunities for data-driven decision-making (Constantiou & Kallinikos 2015). However, with the help of powerful business warehouse solutions, companies have already been able to analyze vast amounts of data. According to scientists like Belanger and Xu (2015), the opportunity to combine data from a multitude of unrelated data sources is central to big data's potential. This characteristic provides the opportunitiy to improve the representation of reality and facilitating the recognition of new, previously unpresentable relationships and patterns (Belanger & Xu, 2015). Of course, combining a small set of data in variousdifferent formats has been, was also already done for years in the past.

Against this background, I support the view that big data is valuable for firms when they have datasets that can be characterized by all four Vs. As Goes (2014, p. vi) pointed out, big data should not be focused on only one dimension, as "*the new paradigm comes by combining these dimensions. The hard core science disciplines have been working on volume and perhaps velocity, but it's the 4 V's together*."

In addition, by working with experts in the field of BDA, I recognized that many experts consider data as big data only if it originates from external data sources. This discussion is also being taken up by different researchers, e.g., Baesens et al. (2016). Associating big data only with data from external sources diminishes the value of BDA, as this definition ignores internal sources like mails, contracts, voice records, and data generated by products equipped with sensors. These kinds of data also occur in high volumes, velocity, variety, and veracity and support the generation of insights (Baesens et al. 2016). Big data should not be differentiated by its sources, a view that is in line with George et al. (2014, p. 321), who described big data as being "*generated from an increasing number of sources of sources, including Internet clicks, mobile transactions, user-generated content, and social media as well as purposefully generated content networks as sales queries and purchase transactions*."

While the term "big data" is clearly defined, the question is why "analytics" was added to big data. I refer to Chen et al. (2012), who argued that BDA should be used as an umbrella term to describe the processes, methods, and technologies for collecting, processing, and analyzing big data. Although many articles about BDA, especially those published by software vendors, give the impression that the technologies and methods for collecting, processing, and analyzing big data constitute an information technology revolution, from my point of view, these technologies and methods are an evolutionary stage of business. This view is also supported by the scientific literature (e.g., Debortoli et al. 2014). However, besides specific technologies like application programming interfaces (API) for data collection, data lakes for data storage, and Hadoop for data processing and analysis that differentiate BDA from conventional business intelligence and analytics initiatives (Chen et al. 2012, Chen et al. 2015, Porter & Heppelmann 2015), we should also consider new methods for analyzing collected data (Baesens et al. 2016). Data analytics once focused primarily on descriptive analytics to answer questions about why something happened (Baesens et al. 2016). Today, data analytics and data scientists conduct predictive and prescriptive data analysis to create insights into what will happen and what to do in future situations (Baesens et al. 2016, Lavalle et al. 2011).

As I discussed with several experts from several companies during a workshop, BDA also refers to a new approach to analyzing data. With the unprecedented opportunities for gathering and analyzing data (Chen et al. 2012), the approach to working with data should be more scientific. Instead of executing analyses in a way that generates pre-defined insights, data scientists need the freedom to explore new data sets with the aim of finding unexpected insights that help to achieve business goals (i.e., service innovation) more effectively. Accordingly, BDA can be extended by an explorative way of analyzing data, an approach that is comparable to that of Netflix. The company honored data scientists who developed the best approach (i.e., algorithm) to improving Netflix's recommendation engine (Davenport & Patil 2012). My insight relates to Baesens et al. (2016, p. 810), who stated, "*State-of-the-art big data research and practice draws on a variety of techniques from machine learning, classical statistics, and econometrics to design of experiments (industry calls this A/B or multivariate testing) to test existing theories and hypotheses, develop new theories, and create large-scale business value*". Accordingly, data scientists get the chance to work in a "real-word laboratory" (Baesens et al. 2016, p. 810) where they can answer a wide variety of new questions.

Against this background, I emphasize that BDA should not be seen as a support function but as an enabler of business process improvements and disruptive innovation.

Three potential uses of BDA

I present three approaches to using BDA for service innovation. The approaches emphasize that the technologies related to BDA enable companies to monitor and analyze a broad variety of external and internal data sources so they can increase their awareness of their customers' behavior, interests, actual context, and emotions and establish innovative behavior-, event-, and emotion-sensitive services that provide new value propositions.

Behavior-based services take into account the insights gained from customers' behavioral patterns, which are leveraged to tailor service-related activities to individual customers. Based on a customer's preferences inferred from his or her behavior, firms can tailor the channel used to promote services to the customer and increase the degree of individualization. The channels' user interfaces can be adapted once—or even dynamically in real time—based on behavioral patterns and the customer's current situation. For example, based on choices that the user makes in navigating a website and the device he or she is using, the user interface can be adapted to shorten the customer's journey to the buy-it-now-option and adapt the functionalities provided to increase simplicity and security.

By establishing behavior-sensitive services, companies can adapt each activity to their customers' preferences, habits, and needs. By providing the customer a highly individualized customer experience, companies can improve their overall service quality and increase the customer's net promoter score and engagement. Moreover, adapting the user interface in real-time to support the customer in shortening the buying process increases the conversion rate and revenue and reduces the required server utilization and operating costs.

In short, behavior-based services enable companies to provide individualized services that are adapted to their customers' interests and preferences. This goal is similar to that of CRM systems, but the intention in using BDA is not only to maximize profit but also to do so by creating a unique customer experience that is informative, convenient, and engaging. BDA is particularly useful when the firm already has a high number of touchpoints that allow it to interact frequently with its customers.

Event-sensitive services refer to services triggered by events, such as a birthday or wedding; specific activities, such as driving on a crowded highway; the condition of a digitized object, such as damages to a car; the external environment, such as weather); or the customer herself, such as health-related events. Companies can also identify future events, but, in general, each event is related to a specific customer need or interest that is triggered by an event that has happened, is happening, or is likely to happen. When these events occur, firms provide helpful interactions (e.g., recommendations, information, and warnings) or take action on the customer's behalf (e.g., starting the sprinkler system in case of a fire).

The difference between event-sensitive and behavior-sensitive services is that event-sensitive services can create new customer touchpoints and new opportunities for interacting with and adding value for the customer. By addressing the customer's need exactly when he or she has a demand, firms improve the customer's experience. Because of the new possibilities for gathering data about customers' everyday lives, BDA allows companies to identify events that go beyond those revealed in a conventional business relationship so they can create new service offers and revenue streams. Companies can also establish a new customer relationship in which they are positioned as the "customer's friend," who offers support in every situation, thereby influencing the customer's perception about the firm and restructuring its branding.

In summary, event-sensitive services enable companies to support their customers proactively exactly when a need or interest occurs and to create new touchpoints that enhance their conventional approaches to customer service. BDA can help companies create a "wow effect" by providing supportive information the customer does not expect, thereby contributing to a unique customer experience and differentiating themselves as a way out of the commodity trap.

Emotion-sensitive services serve the customer in a way that considers her or his affective state. Instead of addressing the customer on a cognitive level by providing behavior- and event-sensitive information, knowledge gained through BDA about the customer's current or future emotional state allows firms to adapt how they "speak" to the customer on an affective level. Thus, firms adjust the content, tonality, channel, or flow of a dialog with a customer or even choose the right front-line employee to deal with the customer. By analyzing customers' statements about the company, such as those made on social media platforms, over a period of time, companies can recognize a customer's moods. For instance, if the customer appears annoyed or dissatisfied, the firm might avoid certain words or topics, instead offering supportive advice or an apology. When the user appears to be pressed for time, the firm may focus on making the interaction short, to the point, and via digital communication, such as text message. In addition, based on historical data, firms can learn about their customers' affective reactions to instances like network failures (in the case of a telecommunications firm) and anticipate how she will feel when failures occur.

By addressing the customer according to her or his emotional state, companies can interact in a way that the customer expects and needs, thereby bringing a personal touch back into mass communication. Making the customer feel understood on an emotional level could makes the firm appear friendlier and more empathic to its customers, improving the customer's perception of the firm. While the other two service-provision practices provide functional value to the customer, emotion-sensitive services promise emotional or hedonic value—the feeling of being understood—which improves customer engagement, acts as a differentiator, and decreases the likelihood of churn.

Emotion-sensitive services enable companies to provide their customers with emotional understanding and support, especially when there is direct personal contact with a service employee. Large numbers of customers, significant time pressure, and increasing amounts of digitalized communication make it all but impossible to create a personal, caring relationship with each customer. Gaining emotional intelligence through BDA can help firms develop an emotional bond with their customers and interact with them as though they were friends.

Implementing BDA – It's not all about technology and data.

Implementing BDA involves not only deciding what technology is needed and which data sources should be used for data gathering but also requires company-wide participation, including stakeholder and management attention (Lavalle et al. 2011). In the following, I give an overview of a systematic approach to realizing the potential of BDA, which consists of three key dimensions: the strategic layer, the organizational layer, and the technological layer.

The strategic layer holds the definition of the strategic framework in which the BDA strategy is connected to the overall corporate strategy and the outcome the company wants to achieve with BDA are described. Accordingly, companies should define the use cases they want to realize with BDA, starting with a list of concrete expectations from relevant stakeholders that can be realized in the short run and the long run. It is important to consider how BDA could be used in an ideal world.

This approach is related to research like that of Lavalle et al. (2011), who argued that one must "*first [define] the insights and questions needed to meet the big business objective and then [identify] those pieces of data needed for answers*" (p. 26). However, as early as 2008, when talking about the use of customer data in general, not about BDA in specific, Piccoli and Watson (2008, p. 113) provided four strategies that enable companies "*to envision how they can adopt the most appropriate strategy (or strategies) for exploiting customer data to improve profitability*." As a first step, they recommended deciding which of the four strategies are most suitable and only then to define the required data sets and technologies.

Customer needs must be taken into account when a company defines the use cases in the context of service innovation (Piccoli & Pigni 2013; Wieneke & Lehrer 2016). Such a customer-centric view enables companies to define use cases that allow them to use BDA to offer their customers the right value propositions (Orlikowski & Scott 2015, Yoo et al. 2012). In addition, creating value for the customers increases customers' willingness to share personal data with the company. Picolli and Pigni (2013, p. 55) also highlighted the use of digital data streams as indispensable for value creation "*to increase customers' willingness to pay for [a company's] product or service or to reduce opportunity cost of the resources it uses to create existing value propositions.*"

I suggest that companies cluster the identified use cases along the three dimensions of behavior-, event-, and emotion-sensitive services) to get an idea of the kinds of use cases that will help them realize their vision. Doing so provides important guidance for the next steps of defining the organizational, technological, and governance requirements and helps to identify potential for uses the company has not considered yet.

The organizational layer consists of the tasks required to set up the BDA team, including how employees should be managed to realize the defined types of use cases, the organizational structure, and the employees' required skill set (Lavalle et al. 2011, Piccoli & Pigni 2013). The organizational structure describes how the company delivers value through BDA that is, how it gathers, processes, analyzes, and uses generated insights in innovating customer services (Wieneke & Lehrer 2016).

As a first step the company highlights the interfaces between the BDA team and relevant stakeholders, including which stakeholders need to communicate with each other and how they will do so. The interface between the business and the BDA team may require a new way of communicating because it must ensure the user-centric work of the analytics team and facilitate the definition of valuable insights (Wieneke & Lehrer 2016) in an environment of high volatility of generated data and fast-changing customer needs (Lavalle et al. 2011, Wieneke & Lehrer 2016). Therefore, communication between the BDA team and the business must be agile, speedy, and customer-centric (Wieneke & Lehrer 2016). In second step, the company defines the required skill sets and roles for the team's employees, determines the number of employees needed, and decides whether external sources should be used for the ramp-up phase and whether it needs to educate its own employees in the field of data science (Lavalle et al. 2011, Piccoli & Pigni 2013).

Finally, in the technological layer, companies should identify from the technical perspective what is necessary to realize the strategic framework, starting by analyzing how their current IT architectures and available data enable them to realize the defined types of use cases. Next, they define the improvements in the current technology and the data management processes. This recommendation is in line with Lavalle et al. (2011), Piccoli and Pigni (2013), and Piccoli and Watson (2008), the last of whom suggest determining the technologies required for analytic needs and the data required to implement the overall strategy. As a last step, the analytics team and the data stewards or chief data officers should decide whether the company needs more data to provide the required insights (Lavalle et al. 2011). New sources for gathering customer data could come from a detailed analysis of the customer's journey and highlighting what kinds of data can be gathered at each touchpoint. They should also check opportunities to use external sources like open data sources.

Summary

BDA is not a technological revolution but an umbrella term for an evolutionary step in the development of business intelligence (Chen et al. 2012). Implementing BDA has many steps that are also necessary in other strategic projects. From my perspective, it is common sense for a company to start by establishing a common understanding of BDA, defining its potential for the company, and finally answering strategy-related, organization-related, and technology-related questions. Moreover, to implement BDA effectively, companies must change their mindsets so employees will be willing to follow the recommendation based on the created insights (Lavalle et al. 2011), as when employees are not willing to accept data-driven recommendations, all the effort spent on the implementation of BDA is useless (Wieneke & Lehrer 2016). Therefore, companies should not neglect the importance of change management (Lavalle et al. 2011).

However, with regard to the new service offers afforded by BDA, I hypothesize that this technological evolution has the potential to revolutionize how companies do business and interact with their customers. Therefore, companies must address the implementation of BDA on a highly detailed and especially customer-centric level.

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