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ORGANIZING INNOVATION

Perspectives on Big Data, Emerging Technologies, and Smart Cities

FrancoAngeli

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CONTENTS

FIGURES

TABLES

1. STEPPING INTO THE FUTURE: THE POWER OF BIG DATA AND EMERGING TECHNOLOGIES

by *Maria Chiara Di Guardo*, *Elona Marku*, *Maryia Zaitsava*[*]

In the twenty-first century, as we enter an era of unprecedented technological innovation and data proliferation, we are not merely stepping; we are leaping into the future. This transition is characterized by the fusion of big data and emerging technologies that are changing the way we work and live. Indeed, in this transformative phase, new technologies enable organizations to provide more efficient and sustainable services, thus opening up new opportunities and fostering exponential growth. In this chapter, we aim to demystify the concepts of big data and emerging technologies, offering a comprehensive glimpse into their current state of development, and highlighting the discourse on ongoing debates. This chapter serves as a foundational stone, designed to deepen our understanding of the important role these technologies play. As we conclude this introduction, we provide a guide, tracing the roadmap of this book, summarizing its structure, and key insights.

1.1. Unlocking Potential: From Big Data to Big Data Insights

Big Data (BD) is no longer a buzzword – it is the lifeblood of our digital existence. With its ability to turn raw numbers into insightful narratives, BD has revolutionized how we interpret and respond to world dynamics (Zaitsava, Marku, and Di Guardo, 2022; Zaitsava et al., 2022). By gathering, processing, and employing data at an unprecedented scale, we are now better equipped to predict trends, make informed decisions, and address complex problems.

BD is commonly defined as large structured and unstructured data sets characterized by high volume, variety, and speed, that require the use of new

[*] Authors are listed alphabetically, they equally contributed to the development of this chapter.

computational techniques to discover trends and patterns within large datasets to enable better decision-making (Chen et al., 2012; George, Haas, and Pentland, 2014; Kwon et al., 2014; Zaitsava et al., 2022). Although, there is no clear definition of the term "BD insights", the understanding of it can be grounded on the BD analytics definition, where outcomes of BD analytics are useful information, such as hidden patterns, and unknown correlations for better decision-making (Chen et al., 2015; Waller and Fawcett, 2013; Vidgen et al., 2017). Therefore, we conceive BD insights as an outcome of the extraction process of the useful meaning from BD using BD analytics, which potentially leads to gaining firms' competitive advantage.

Current studies in innovation management have shown that insights that are meaningfully derived from BD have the potential to transform key business functions and influence whole industries (Appio et al., 2018; Batty, 2013; Chen et al., 2015; Erevelles et al., 2016; Gretzel et al., 2015; Hopkins, 2010; LaValle et al., 2011; Milliken et al., 2014). It has been witnessed that the modern data-driven mode of decision-making is outperforming the classic intuitive school. Specifically, LaValle et al. (2011) argued that so-called top-performers firms tend to apply BD Analytics in their key business-activities, from financial management and budgeting to brand or market management, while low-performers mostly apply intuition as the key source of managerial knowledge. BD insights can support managerial day-to-day operations, but also strategic decisions, such as supply-chain performance, resources, and assets better use, meaningful insights creation is associated with business growth (Chen et al., 2012; Kumar, Niu, and Ré, 2013; LaValle et al., 2011). Also, BD is a source of new knowledge and insights able to provide a certain level of managerial confidence to managers and help them to overcome emotional issues while coping with market uncertainty, especially in a high-velocity market (Chen et al., 2012).

However, the conditions where analytics-driven insights produced via BD can trigger changes across a firm are that BD insights should be related to a business-strategy, easy to understand and consume, and should be timely (LaValle et al., 2011; Wang et al., 2018). Effective insights are not only those created with meaning but also those created at a needed time, leading to fast decision-making. Therefore, on the one hand, such concepts as "actionable", "valuable", "timely", and "analytics-driven" insights went on-stream as the key terms in defining the new practicability aspect of BD insights (Chen et al., 2015; LaValle et al., 2011; Sivarajah et al., 2017; Davenport and Harris, 2017). The research focus is shifting from exploring the issues of data collection, storage, and analysis to the challenge of creating meaningful and actionable insights to support decision-making (Arunachalam et al., 2018; Bharadwaj et al., 2013; Roßmann et al., 2018; Zhong et al., 2015; Vidgen et al., 2017; Wessel, 2016). On the other hand, the need for effective ways to produce this kind of insight to exploit big volumes of data is becoming salient in the management literature (Chen et al., 2015). As the majority of answers result in exploring advanced BD Analytics technologies that enable insights to improve business strategies and the decision-making process (Sivarajah et al., 2017), firms lack efficient mechanisms to turn high volumes of data into meaningful and actionable insights (Gandomi and Haider, 2015). Indeed, the main body of research has been focused on understanding BD Analytics as a source, which is needed to be managed properly to get insights (Sivarajah et al., 2017; Jukić et al., 2015). However, it has been recognized that BD Analytics is only a sub-process in the complex process of meaningful insights extraction (Gandomi and Haider, 2015; Labrinidis and Jagadish, 2012).

Moreover, BD as a field lacks an understanding of what is managerial and organizational challenges while using BD (Simsek et al., 2019), however, several key points restrict the ability of managers to fully recognize the potential of BD and BD insights (Zhang, 2019). Thus, Court (2015), highlighted that managers do not appreciate the opportunistic approach of data scientists or vendors in finding "any possible meaningful insights and patterns" to drive changes in an organization, as these open-ended insights lack strategic orientation and do not lead to large-scale changes at the end. Managers are not confident that BD can improve their decision-making, as they simply do not understand insights, patterns created, and recommendations suggested by "statistically heavy" analytics. BD insights, therefore, seem them a black box (Zaitsava et al., 2022).

1.1.1. Moving the Focus towards Higher Quality of Big Data Insights

In the attempt to investigate the phenomenon of BD, existing literature conceived BD in terms of its primary features or dimensions. With the advance of technology in BD, the merely computational view of BD is decreasing its popularity as it depreciates its strategic significance (Yoo, 2015). The new tendency coming mostly from practitioners (Schroeck et al. 2012; Dijcks, 2012) breaks the established mathematical approach and adds new strategic-oriented dimensions raising the attention of strategy scholars. Hence, the discussion focus shifts from the phenomenon of BD to BD quality of insights, viability, benefits, and values (Urbinati et al., 2019).

More specifically, Laney (2001) in his seminal work proposed a "3Vs" approach where *Volume*, *Variety,* and *Velocity* are the core characteristics of

BD; this view was supported by scholars of different fields, including technology innovation and information systems (Chen et al., 2012; Gandomi and Haider, 2015; Ghasemaghaei et al., 2018; Kwon et al., 2014, Al Nuaimi et al., 2015; Urbinati et al., 2019). In particular, the concept of *Volume* encompasses the magnitude of data and as such, it was for a long time considered the key and dominant characteristic of BD (George et al., 2014; Frizzo-Barker et al. 2016; Seddon and Currie, 2017). This inclination came from the misnomer of BD, where "Big" reflects only the volume side of data, which misled in this way the researchers (George et al., 2014, Yoo, 2015). Moreover, large data-sets per se do not make BD interesting and insightful (Chen et al., 2012; Sivarajah et al., 2017; Yoo, 2015). Even though *Volume* has been mainly perceived as a purely quantitative dimension, increasing large-scale data, paradoxically opens up new opportunities for digging into the qualitative side of the *Volume* of BD that is made possible by the adoption of new advanced techniques, analytics models, and algorithms.

BD is not only about the size of data, as observed by both academics and practitioners, BD is generated from a dramatically increasing variety of sources from social data to transactional and machine data; it can have different shapes, to name a few such as text, audio, video, numbers, images, web logs, scientific data, user-generated content. All these build the second dimension of BD, namely, *Variety* (Gandomi and Haider, 2015). The importance of the *Variety* of BD cannot be underestimated, as this richness of data sources leads to more sophisticated insights, which previously could have been missed due to the narrow and focused nature of data (George et al., 2014). This shift from the number of sources towards the so-called granularity of BD – or the ability of BD to provide fine-grained insights using different data sources – has started gaining more attention within the discussion on the *Variety* of BD (Günther et al., 2017; Yoo, 2015).

Also, the concept of *Velocity* reflects the speed with which BD is generated (Sivarajah et al., 2017). A crucial aspect of the speed is that BD is not occasionally generated, but it is harvested in a continuous mode (Kitchin and McArdle, 2016). Thus, on the one hand, real-time data generation captures, to some extent, the degree of quality that makes BD different from statistics, surveys, and archival data sources that remain mainly static (George et al., 2014), while on the other hand, it helps to reveal hidden trends and latent patterns by applying computational approaches. Consequently, the exponential growth of real-time BD has triggered the need in enhancing real-time analytics (Gandomi and Haider, 2015). Recent technology innovation studies highlighted the importance to explore other kinds of *Velocity*, the speed of acting upon BD Analytics (Gandomi, and Haider, 2015), and the issues related to BD decay or the declining value of data over time (Lee, 2017).

With the rise of multiple data sources, the need to neglect uncertainty and work with trustworthy data is becoming crucial (Gandomi and Haider, 2015; Schroeck et al. 2012). In addition to the changes occurring within the three dimensions mentioned above, recent studies have introduced a fourth dimension, namely *Veracity* of BD conceived as the ability of BD to provide reliable insights (Schroeck et al. 2012). This dimension becomes even more salient as the decision-making performance depends on the presence or absence of high-quality data in terms of timing and relevance (Ghasemaghaei et al., 2019; Lee, 2017; Sukumar and Ferrell, 2013). Paradoxically, despite the growth of the diversity of BD sources, the easiness to access BD and reuse it is triggering the emergence of the attitude of use without a prior clearly defined goal and/or strategy that might lead to a “fad” phenomenon (Günther et al., 2017; Constantiou and Kallinikos, 2015; Simsek et al., 2019). In so doing, the inductive approach to BD use definitively affects the ability to generate meaningful insights (Günther et al., 2017). In this perspective, the variety of data sources should be supported by a certain level of trust in the pluralism of data channels (Wamba et al., 2017).

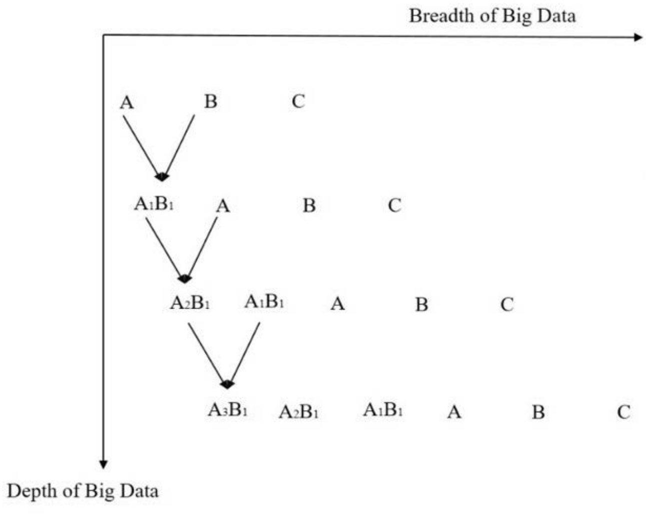
Finally, the fifth BD dimension, namely *Value*, is rather a desirable outcome of BD than quality (Gandomi and Haider, 2015; Uddin and Gupta, 2014). The challenge of BD to translate insights into values and analyze BD in a way that brings big value has started gaining attention in managerial literature, highlighting the need for further qualitative and quantitative investigations (LaValle et al., 2011).

1.1.2. Understanding the Effects of Big Data

Following the latest development in the innovation management literature (Zaitsava et al., 2022), in this section we present a conceptualization of the BD effects. More specifically, the dimensions *Volume* and *Variety* have the same sub-dimensions, namely, *breadth* and *depth*, which do not work for the other two dimensions. In turn, *Velocity*, and *Veracity*, while not having the same sub-dimensions, still share common features. Sub-dimensions shape the overall traits of their head dimensions negatively or positively. This prompted us to go deeper into the shared similarities and differences between BD dimensions and conceptualize them into two effects, namely, *Proliferation* and *Additive*.

Volume and *Variety* are able to generate what we called a *Proliferation* effect (see Figure 1.1), defined as an exponential growth of BD that goes through a process of data fusion boosted by division and recombination of different levels of data source(s). Indeed, division and recombination are two core properties of the *Proliferation* effect that distinguish it from the *Additive* effect. The *division property* refers to the ability of BD to be split into autonomous portions of data that can be manipulated for producing new output. In its turn, *recombination property* refers to the ability to recombine various autonomous portions of data in a meaningful way. In other words, *Volume* and *Variety* grow or proliferate with the division and recombination of datasets. The *Proliferation* effect comprises the ground for the *Volume* and *Variety* dimensions' performance, not only influencing the breadth of Volume and Variety of BD (number of data variables and sources) directly but also the *depth*, as with data division and recombination more sophisticated and synthetic outputs come out.

Figure 1.1 – Proliferation effect of Volume and Variety



Conversely, *Velocity* and *Veracity* have an *Additive* effect (see Figure 1.2) defined as the performance of all sub-dimensions acting together is equal to the sum of each sub-dimension taken separately. Adding or disregarding one, several, or all facets of *Veracity* or *Velocity* affects positively or negatively, respectively, the overall performance of *Veracity* and *Velocity*. For example, by respecting all sub-dimensions of the *Veracity* (e.g., targeting, technical specifications, error-free data analysis, or up-to-date data), it is possible to reach a high level of BD reliability, while disregarding at least one of the facets that leads to the lowering of BD trustworthiness. Similarly, having all four facets of *Velocity* (data generation, fusion, visualization, and use speed) at a high-speed rate will increase the overall speed of the *Velocity* dimension.

Figure 1.2 – Additive effect on the example of Velocity dimension

1.2. The Dawn of Tech: Exploring the Emergence of Technology

Emerging technologies are an essential driver of economic growth and a key promise for society (Schumpeter, 1934; Dosi, 1982; Freeman and Soete, 1997; Kapoor and Klueter, 2020). The concept of emergence comes from the Latin *emergere* – "to bring forth, to bring to light" – and refers to the process of coming into being or starting to exist. In particular, the inception of new technology is often characterized by high uncertainty as some technologies might prosper while others fail (Adner and Levinthal, 2002). This specific dynamic makes more salient an in-depth investigation of the earliest signals and underlying conditions that might lead technology to follow a particular route.

Existing literature on technology emergence has addressed several aspects including technology origins and nature (Levinthal, 1998; Corrocher et al., 2003), patterns and trajectories of technology emergence and its further development (Dosi, 1982; Anderson and Tushman, 1990; Henderson, 1995; Kapoor and Klueter, 2020), and the impact of new technology on competition, economy, and ultimately, society (Freeman and Soete, 1997; Allen et al., 2020).

More specifically, the nature of new technology refers to the explicit features of the knowledge sources embodied in that technology. The distinct nature delineates the pedigree or traits of technology knowledge, influencing technology's first appearance and subsequent growth (or failure). Basalla (1988; p. 141) noted that "When an invention is selected for development […] each invention offers a spectrum of opportunities, only a few of which will ever be developed during its lifetime." New technology may stem from a single idea or the convergence or fusion of different ideas from different technological domains (Corrocher et al., 2003; Levinthal, 1998).

Moreover, decades of research have offered different theoretical perspectives to explain how technology emerges and further develops. Some studies have conceived technology emergence as a smooth and cumulative flow of technical, institutional, and social change (Dosi, 1982; Rosenbloom and Cusumano, 1987; Basalla, 1988; Corrocher et al., 2003). Frameworks such as the S-shaped pattern of technology performance exhibit improvements to occur, gradually accumulating knowledge (Dosi, 1982; Henderson, 1995). On the contrary, other studies have highlighted that technology emergence and change are rapid and discontinuous offering the metaphor of "waves of creative destruction" (Tushman and Anderson, 1986; Schumpeter, 1934). Nelson and Winter (1982) and Malerba and Orsenigo (1995) have shown that the change process in all industries can be explained by both creative destruction and creative accumulation. In an attempt to reconcile these two perspectives, scholars have introduced the concept of punctuated equilibrium (Tushman and Romanelli, 1985; Tushman and Anderson, 1986). This cumulative process is often interrupted by major progress and technological challenges or "setbacks," which outline the industry's R&D efforts toward technological advance (Tushman and Anderson, 1986; Kline and Rosenberg, 1986; Kapoor and Klueter, 2020). Indeed, emergence and evolution often do not show flat and well-behaved patterns, but they are characterized by complexity and disorder with pitfalls and failures (Kline and Rosenberg, 1986; Kapoor and Klueter, 2020).

Also, the Schumpeterian view highlights that technological improvements have an economic impact when applied to different contexts and are built upon original and novel ideas. Expansion and growth require new technology configurations and re-configurations while adapting and re-adapting according to internal and external signals of both science and the market (Hekkert and Negro, 2009; Markard and Truffer, 2008; Van Merkerk and Smits, 2008, Van Merkerk and Robinson, 2006; Marku, 2019). Studies have highlighted that the higher the generality of these technologies, the higher their impact will be (Martin, 1995). In the same vein, novelty is a fundamental feature that fosters economic impact and growth (Small et al., 2014). Other criteria have been proposed for the identification of new technologies with the highest impact, for instance, those allowing a drastic cost reduction, huge technical improvement, acceptability, and pervasiveness (Freeman, 1985).

According to Rotolo, Hicks, and Martin (2015), an emerging is defined as "a relatively fast-growing and radically novel technology characterized by a certain degree of coherence persisting over time and with the potential to exert a considerable impact on the socio-economic domain(s) which is observed in terms of the composition of actors, institutions and the patterns of interactions among those, along with the associated knowledge production processes. Its most prominent impact, however, lies in the future and so in the emergence phase is still somewhat uncertain and ambiguous".

An emerging technology is characterized by five attributes, namely, radical novelty, relatively fast growth, coherence, prominent impact, and uncertainty and ambiguity (Rotolo et al., 2015). Radical novelty can manifest as "dis-continuous innovations born from radical innovations" (Day and Schoemaker, 2000). This newness is not restricted to one aspect of technology but could be seen either in the approach applied or in the function of the technology itself. The relatively fast growth feature serves as a key indicator in observing the evolution of a technology (Srinivasan, 2008; Cozzens et al., 2010; Small et al., 2014). Coherence, in the context of an emerging technology, refers to the intrinsic traits of a collective, including aspects like cohesion, unity, logical interconnection, and congruity. However, this is not limited to internal characteristics; external relations also play a significant role. The attribute of prominent impact relates to the effect on the entire socio-economic system, aligning with the concept of "general purpose technologies." This widespread influence emphasizes their transformative potential and the ability to reshape the landscape of our society and economy. Finally, uncertainty is an inherent aspect of the emergence process due to its non-linear, multifactorial nature. This feature captures the potential that emerging technologies possess to transform the prevailing ways of doing things (Hung and Chu, 2006).

1.3. Mapping the Journey: Book Structure and Key Insights

This book embarks on a journey into BD and emerging technologies, exploring how the two are currently reshaping our landscape by yielding a new era of smart cities. It is an evolution that blends the tangible with the intangible, the present with the future. These transformative phenomena offer readers a fresh, thoughtful perspective on the powerful forces at work while organizing innovation.

In the first chapter, we included core concepts that guide the reader into the complex and rich world of BD and emerging technologies. Indeed, Chapter 1 covers core definitions and key conceptualizations that are subsequently disentangled.

The second chapter of the book delves into the potential of BD, with a particular focus on data-driven insights for effective decision-making and management of innovation in smart city projects. It presents a compelling case study of a large international pilot, the Active Travel Insights (ATI)