

Intellectual capital in the era of Big Data

الضخمة البيانات عصر في الفكري المال رأس

ASSI Zahra Narimene¹

¹Oran Graduate School of Economics, LAMAPE Laboratory, Algeria,
zahranarimene.assi@ese-oran.dz / assi.narimene@gmail.com

Received: 25/11/2023

Accepted: 21/11/2024

Abstract :

In today's economic landscape, where intangible assets play a predominant role, companies' competitive advantage is increasingly based on their intellectual capital. This trend is further amplified by the exponential growth in the volume of data in circulation, a phenomenon known as Big Data. This paper aims to shed light on the Intellectual Capital (IC) transformation —via its various dimensions: human, structural, and relational— following the integration of massive data and associated storage and processing technologies within companies.

Keywords : big data, intellectual capital, human capital, structural capital, relational capital

Jel Classification Codes : 034 ; M15

ملخص :

لـ كـشـبـ تـاـكـرـشـلـا سـفـانـتـ دـمـتـعـيـ، اـزـرـابـ اـرـود تـسـومـلـمـا رـيـغ لـوـصـلـا بـعـلـتـ تـيـد ،يـلـا حـلـا يـدـا صـتـقـلـا دـهـشـمـلـا يـفـ تـاـنـا يـيـلـا مـجـد يـفـ لـنـا هـلـا و مـنـلـا عـم يـفـا ضـا لـكـشـب مـر يـثـا د يـا ز تـيـ مـا جـتـا و هـو ،يـر كـفـلـا لـا مـلـا سـأ ر يـلـا د يـا ز تـم يـلـا تـيـحـبـلـا تـقـر و لـا مـذ ه فـد هـت ،قـا يـسـلـا ا ذ ه يـفـ .تـمـخـضـلـا تـاـنـا يـيـلـا حـلـطـصـمـب تـقـفـور عـمـلـا تـقـر هـا ظـلـا و هـو ،تـلـو ا د تـمـلـا - تـيـتـا قـلـا عـلـا و تـيـلـك يـهـلـا و تـيـر شـبـلـا :تـد د عـمـلـا مـد ا عـبـا لـلـا خ نـم - يـر كـفـلـا لـا مـلـا سـأ ر لـو حـة يـلـا عـو ض ط يـلـسـت لـخـاد ا هـتـجـلـا عـمـو ا هـنـيـز خـتـب تـلـصـلـا تـا ذ تـا يـنـقـتـلـا و تـمـخـضـلـا تـاـنـا يـيـلـا حـمـد لـا تـج يـتـد الشـر كـات .

كلمات مفتاحية : لـا مـلـا سـأ ر ،يـلـك يـهـلـا لـا مـلـا سـأ ر ،يـر شـبـلـا لـا مـلـا سـأ ر ،يـر كـفـلـا لـا مـلـا سـأ ر ،تـمـخـضـلـا تـاـنـا يـيـلـا يـقـنـلـا عـلـا

تصنيف JEL : 034 ; M15

Introduction:

As the various industrial revolutions have progressed, the intensity of competition has increased at the same pace as the proportion of intangible assets in the economy. Global society is living in a knowledge-based economy, in which physical assets are no longer sufficient to guarantee companies a competitive advantage. Intellectual capital (IC) is therefore becoming an increasingly important source of value.

In this contemporary knowledge economy, big data is one of its most representative paradigms (Secundo et al., 2017). This phenomenon, which refers to the exponential growth in the volume of data in circulation, multiplied by more than thirty over the last decade (UNCTAD, 2021), is leading to a veritable data revolution (Macfeely, 2020), impacting markets, organisations and relationships (Mayer-Schönberger & Cukier, 2013).

Although companies have always relied on data, the importance attached to it is taking on a whole new dimension with the emergence of big data, which is bringing with it new capabilities that are raising many questions about its repercussions on companies' strategic assets, particularly intangible ones, in both professional and academic circles.

Indeed, after going through several phases, ranging from descriptive discussions of its importance for the organisation, centred on strictly monetary value creation, to taking stakeholders and wider value into account (Dumay, 2016), the literature on IC is currently entering the fifth phase of research based on the integration of big data and artificial intelligence (Harlow, 2018). In this context, the need for research exploring the repercussions of such phenomena on IC components has been clearly stated in the literature (Erickson & Rothberg, 2018; Secundo et al., 2017).

This paper is precisely in line with this and aims to shed some theoretical light on how the integration of big data technologies impacts a company's IC. To achieve this, we first intend to trace the evolution of the concept of IC up to its current state of the art and to highlight its component dimensions. We will then attempt to grasp the phenomenon of big data from a technological and managerial perspective. Finally, we will analyse the links between these two concepts in order to identify the changes brought about by big data and thus offer insights into how companies can optimally leverage its potential in harmony with existing intangible resources.

1. Intellectual capital:

1.1. Roots of the concept:

The concept of IC is derived from the concept of knowledge, which is not new to economic literature and dates back to the seminal work of economists such as Marshall who affirms that knowledge is the “most powerful engine of production” (Marshall, 1965, as cited in Nahapiet & Ghoshal, 1998).

This perspective is also shared by Arrow (1962), who asserted the importance of knowledge in the economic sphere by focusing his analysis on experience or learning by doing, and is at the core of Schumpeter's work on economic development which is, according to him, the result of successive innovations driven by knowledge (Schumpeter, 1983).

In the management literature, knowledge has been central to the evolutionary theory which considers the firm as a repository of knowledge, particularly through the routines that are created within it (Nelson & Winter, 1982, as cited in Becker, 2004), and the knowledge-based theory (Grant, 1996), which recognises the role of knowledge a key resource for obtaining a competitive advantage. The concept of IC was subsequently introduced by Galbraith and expanded upon by Drucker in his description of what he termed the post-capitalism society (Bontis, 2001).

1.2. Definition:

Originally extracted from accountability, the notion of IC focuses on the recognition and measurement of an organisation's knowledge assets (Erickson & Rothberg, 2018). Even if Secundo et al. state that "IC is a multi-faceted and elusive topic" (2017, p. 245), it is worth noting that there is a near-consensus among authors in the literature regarding its definition. They agree that it mainly refers to knowledge and intangible assets that enable wealth to be created.

However, certain differences need to be highlighted regarding its composition: on one hand, some authors define IC in the strict sense by directly associating it with knowledge, such as Edvinsson and Sullivan who claim that IC is "knowledge that can be converted into value" (1996, p. 358).

Others, such as Dumay (2016) who based on the work of Stewart (1997), view IC as a broader concept, including not only knowledge but also "[...] intellectual material, knowledge, experience, intellectual property, information [...] that can be put to use to create value" (Dumay, 2016, p. 169).

On the other hand, some authors have chosen the broadest sense of the term and group under it all kinds of intangible assets such as processes, innovation capacities, tacit knowledge, partners networks, etc. This is the case of Nahapiet and Ghoshal who define IC as "the knowledge and knowing capability of a social collectivity, such as an organization, intellectual community, or professional practice" (1998, p. 245).

In relation to this last point of view, also shared in this paper, it is therefore generally accepted that IC is made up of three dimensions: Bontis (1999) considers it as a second-order multidimensional construct including the human, structural and relational dimensions.

According to Guthrie et al., human capital is “the knowledge embedded in people” (2012, p. 70). It has been defined, on an individual level, as composed of four factors: i) genetic inheritance; ii) education; iii) experience; and iv) attitudes about life and business (Hudson, 1993, as cited in Bontis, 1999). Bontis (1998) explains that the essence of human capital is inherent in employees, consisting of a type of knowledge that is predominantly tacit and difficult to codify.

Structural capital, which refers to “the knowledge embedded in the organisation and its systems” (Guthrie et al., 2012, p. 70) has been defined by Edvinsson and Sullivan as “the infrastructure that firms develop to commercialize their human capital” (1996, p. 360). It contains the organisation mechanisms and structures, which can be divided into two categories: technological (e.g. tacit knowledge and usage rules) and architectural (e.g. culture and routines) (Bontis, 1998).

Relational capital represents “the knowledge embedded in customers and other relationships external to the organisation” (Guthrie et al., 2012, p. 70). It encompasses knowledge concerning external relations of the organisation with its stakeholders, including customers, suppliers and regulators. Bontis (1998) argues that it is the most difficult of the three sub-domains to develop since it is the most external to the organisation.

1.3. Stages of IC research:

Research on IC has evolved through five distinct stages in the literature. The first includes research during and prior to the mid-1990s (Petty & Guthrie, 2000) which has been mainly driven by the work of practitioners in the field. These studies were mainly descriptive and non-empirical, aimed at raising awareness and understanding of the IC’s potential (Harlow, 2018).

The second stage concentrated on addressing this lack of empirical validation. It contains investigations that focused on the “how” question (Petty & Guthrie, 2000, p. 162), by exploring the process of value creation facilitated by IC. Numerous evaluation methods were developed, making it one of the most productive stages and closely related to strategic management (Secundo et al., 2017).

The third research stage began in 2004 (Busso et al., 2021), and took a critical and performative approach to analysing IC practices in action (Guthrie et al., 2012). During this stage, the notion of IC has evolved, moving from a static to a dynamic system of intangible resources, and shifting focus to the interactions between IC components and the activities involved in managing these assets (Secundo et al., 2017).

The fourth stage is characterised by moving beyond the organisation’s boundaries, incorporating stakeholders, and transitioning from a managerial to an ecosystem perspective (Busso et al., 2021). It included other forms of value, beyond exclusively monetary wealth (Dumay, 2016), and emphasised the existence of knowledge beyond the organisation—a key aspect of the relational dimension of IC (Secundo et al., 2017).

The fifth and final stage, in which this research is situated, has been recently introduced by Harlow who claims that “[it] relies on using AI [Artificial Intelligence] and BDA [Big Data Analytics] to develop IC by focusing on the SI of the firm” (2018, p. 401), and is therefore suitable for exploring data-enabled organisations based on big data, and the challenges the latter imposes for the management and disclosure of IC.

2. Big data, from a technological to a managerial phenomenon:

2.1. From data to “big data”:

From a conceptual point of view, “big data” primarily refers to data, which is defined in the literature as “a description of something that allows it to be recorded, analyzed, and reorganized.” (Mayer-Schönberger & Cukier, 2013, p. 78).

From a technological perspective, data is a binary combination that can be processed by machines, whereas it is considered in the information sciences to be the foundation of information and knowledge, as described in the knowledge pyramid (Ackoff, 1989, as cited in Bellinger et al., 2004).

From an economic point of view, data is conceptualised as an economic good characterised by: i) immateriality (UNCTAD, 2021; Coyle et al., 2020); ii) non-rivalry (Jones & Tonetti, 2020); iii) non-excludability when it is public data, or partial-excludability when it is possible to prohibit or restrict access to it by certain economic agents, notably by legal or technical means (Coyle et al., 2020); and iv) economic externalities (UNCTAD, 2021).

Data is born through a process of abstraction, known as “datafication” (Mayer-Schönberger & Cukier, 2013, p. 18). This process, which is becoming increasingly intense due to increases in telecommunications bandwidth and the capacity of storage and computing systems (Hilbert, 2016), has given rise to the phenomenon called “Big Data”.

As asserted by Mayer-Schönberger and Cukier (2013), there is no rigorous definition of big data. However, its characteristics offer a common framework for delimiting its content. Three main characteristics, known as the “3Vs” (Laney, 2001, as cited in Curry, 2016), are inseparable from the definition of big data: i) volume, referring to the size and amount of data which is beyond the ability of common software tools (Bharadwaj et al., 2013); ii) variety, including structured and unstructured data (McAfee & Brynjolfsson, 2012); and iii) velocity, denoting the speed of data generation, often dynamic and near real-time (Kitchin, 2014).

The “3Vs” represent the fundamental and most commonly cited characteristics. Yet, other authors (Miele & Shockley, 2013) add a fourth “V”, designating veracity, or validity, concerning the quality of the data collected; while others, such as Wamba et al. (2014), mention “5Vs” by adding value, referring to the economic benefits that can be extracted from these data. According to Ciuriak (2019), these benefits arise from the creation of information asymmetry, machine learning, machine knowledge capital, process optimisation and consumer surplus.

Finally, a smaller subset of authors (Gandomi & Haider, 2015) mentions a sixth “V”, relating to variability, in reference to the variation in data rates.

2.2. Big data, beyond the technical scope:

Beyond these characteristics, big data should also be understood from a managerial and organisational point of view: indeed, Boyd and Crawford (2012) consider big data to be a cultural, technological and scientific phenomenon involving technologies, analysis and a belief in the informational power of data. In the same vein, Wamba et al. (2014) perceive it as a holistic approach dedicated to managing, processing and analysing data characterised by the 5Vs in order to create value and build competitive advantage, while McAfee and Brynjolfsson (2012) even mention a “management revolution”.

For example, Davenport et al. (2012) suggest that big data has the following impacts: the organisation no longer focuses on data stocks but on data flows; it relies more on data scientists, product and process developers rather than data analysts; and data analysis is integrated throughout the organisation and is no longer confined to the IT department.

In this regard, Hilbert states that “the full name of Big Data is Big Data Analytics” (2016, p. 139) in order to highlight that this concept goes beyond the questions about data quantity and quality and focuses primarily on its analysis for informed and enhanced decision-making.

De Mauro et al. has thus mentioned that big data “requires specific technology and analytical methods for its transformation into value” (2015, p. 103). Indeed, Comuzzi and Patel (2016) identify two main aspects closely tied to big data: the first relates to the storage and processing of large volumes of data, and the second relates to analysis techniques, and the hardware and software infrastructures they require, in order to extract information from them. Therefore, for the purposes of this article, we encompass under the term “big data” not only a specific type of data, but also the technologies and methods it entails.

It is also important to note that successfully integrating big data into a company necessitates considering the organisational changes it brings about. In our research, we are specifically focusing on the changes to IC.

3. Big data and intellectual capital:

Since data is the basis of knowledge, “a natural connection exists between KM [Knowledge Management], IC, and the burgeoning trend toward the application of big data and business analytics.” (Erickson & Rothberg, 2014, p. 114).

Consequently, the literature widely acknowledges that big data offers numerous opportunities for supporting the implementation of IC in all its components. For instance, Secundo et al. (2017) explain that the data constituting big data itself relates to the three categories of IC: data on employees and collaborators enhances human capital, data on consumers, suppliers and competitors contributes to relational capital, while data on tangible and intangible infrastructures consolidates structural capital.

We propose to examine the relationship between big data and IC based on the model developed by Harlow who states that “IC is the resultant unique and valuable rent-making of the BDA knowledge”, (2018, p. 401). Harlow's approach emphasises the importance of a knowledge management strategy (KMS). The author suggests that companies should develop such a strategy in order to leverage data analytics for uncovering IC knowledge. According to him, “KMS fulfils a key role in the development of information from data, along with the development of knowledge and IC from that information” (Harlow, 2018, p. 402).

Indeed, on the one hand, big data is considered to contain tacit knowledge (Kabir & Carayannis, 2013), a perspective shared by Erickson and Rothberg (2014) who describe data as a “preknowledge” that can significantly contribute to knowledge management. On the other hand, knowledge management describes “the panoply of procedures and techniques used to get the most from a firm's knowledge assets” (Teece, 2000, p. 35), it allows “to capture, distribute, and effectively use knowledge” (Davenport & Prusak, 1998, as cited in Carlucci et al., 2004, p. 579), and thus facilitates the accumulation and development of IC within the organisation (Seleim & Khalil, 2011).

In this respect, Harlow's model, which is based on the “Big Data/Analytics-Knowledge Management System” model of Pauleen and Wang (2017), suggests that the relationship between big data and IC can be viewed as a value chain wherein data is converted into information and subsequently into this capital.

A Data Value Chain (DVC) is defined by Kaiser as: « a model to describe data flows as a series of steps, each of them transforming the value of data » (2019, p. 71). Based on Ackoff's Data-Information-Knowledge-Wisdom (DIKW) hierarchy (1989), Jony et al. (2016) propose a three-stage value chain, starting with questions about data sources, type and accessibility; followed by the pre-processing and storage stage, which corresponds to the “information” part of the pyramid and involves data extraction and transformation (cleaning, coding, aggregating, splitting), and loading into the database; and, finally, the processing or analysis and visualisation stage, corresponding to the “knowledge” and “wisdom” part of the pyramid, which entails descriptive, diagnostic and predictive or prescriptive analyses.

3.1. Big data and human capital:

Big Data makes a considerable contribution to the development of human resources (Garcia-Arroyo & Osca, 2021), which has long been recognised as a determining factor in the accumulation of human capital (Garavan et al., 2001).

De Santis and Presti (2018) highlight that the integration of big data impacts human capital in four major areas: talent acquisition, employee retention, decision-making, and skills improvement.

In relation to the first point, Hamilton and Sodeman (2020) explain that a major use of big data is dedicated to the selection of candidates during the recruitment process, through the use of software to sort applications and data extracted from public databases, enabling predictive models to be developed and thus ensuring to hire the most appropriate profiles.

Similarly, employee retention can be managed using specialised algorithms (Singh et al., 2022). Data analysis, by cross-referencing different sources, could thus help to detect the “knowledge stars in the firm who disproportionately offer exceptional knowledge, innovative ideas, and skills to the organization” (Hamilton & Sodeman, 2020, p. 91).

In terms of decision-making capacity, La Torre et al. (2018), referring to decision theory, explain that big data, through the collection of data in real time and the development of analytical capacities, enriches both the content and the scope of decision, which in turn enables timely and customised decisions for different organisational purposes.

However, Hamilton and Sodeman (2020) caution against limiting the use of big data to administrative effectiveness, and stress that it should be aimed at enhancing the skills and knowledge of employees. In this context, Sena and Ozdemir (2020) point out that investment in information and communication technology (ICT) can only lead to a positive return for the company if it is accompanied by investment in a skilled workforce. In this regard, the adoption of big data technologies can significantly contribute to strengthening the learning process within the organisation (De Santis & Presti, 2018), and improving the skill level of the employees (Raguseo, 2018). This, in turn, can have a favourable impact on education and experience within the organisational context.

3.2. Big data and structural capital:

Hussain et al. (2023) state that, according to the theoretical concept of the resource-based theory, big data analytics can be considered as an organisation technological capability to record, store, analyse, assess, monitor and control information at each stage of the work process.

Big data considerably enriches an organisation's database, providing substantial support for effective knowledge management strategy (Harlow, 2018). Moreover, it provides a flexible informational infrastructure throughout the company, transforming conventional processes into communicative and interconnected ones, which, in turn, promotes transparency and fluidity in the circulation of information (Brown et al., 2011).

Data can also be mobilised for decision-making or incorporated into organisational intelligence as a latent routine for potentially using it in subsequent decisions (Merendino et al., 2018). As described by Miller and Mork (2013), big data technologies enable the collection, aggregation and integration of data from different departments.

This results in a comprehensive data overview that reveals essential insights for informed decision-making (Miller & Mork, 2013), and improves internal processes (Wixom & Ross, 2017), particularly through predictive and prescriptive analyses, making them shift from intuition-driven to data-driven processes (Fredriksson, 2015, as cited in De Santis & Presti, 2018). This integration of data into processes forms the basis of what Hupperz et al. (2021) describe as a “data-driven organisation”.

Also, De Santis and Presti (2018) assert that the effect of Big Data on the learning process enables the formalisation of individual knowledge, inherent in human capital, into more structured knowledge found in organisational routines, which constitute a significant part of the structural capital.

3.3. Big data and relational capital:

On the one hand, big data is largely made up of customer and transaction data (Veldkamp & Chung, 2019). In this respect, Erevelles et al. (2016) evoke the term “big data consumer analytics” which they define as “the extraction of hidden insight about consumer behavior from Big Data and the exploitation of that insight through advantageous interpretation” (Erevelles et al., 2016, p. 897).

Consequently, big data provides rich insights about customers, facilitating the identification of their needs and enabling market segmentation (Wamba et al., 2014). Zerbino et al. (2018) have also highlighted various applications of big data throughout the customer relationship management process, including: customer profiling, customer journey evaluation, analysis of customer dissatisfaction, churn analysis, implementation of recommender systems, etc.

All these elements enhance the knowledge about customers and allow for personalised relationships, which in turn generate additional data, and continually strengthen relational capital.

On the other hand, in terms of relational capital related to the company's partners, the integration of big data technologies makes collaborative relationships more prevalent (Lacam, 2020). These relationships often take the form of a specific ecosystem, representing an economic community founded on interdependencies among the actors that constitute it (Moore, 1996, as cited in Curry, 2016), and through which partner companies exchange data and analytical and storage capacities.

Gelhaar et al. (2021) precise that a data ecosystem is thus specific in describing the interactions taking place between certain players dedicated to data and associated technologies. Within this environment, various actors play distinct roles: data providers, comprising the individuals and organisations supplying the raw data; data intermediaries; and consumers or end users of the data (Oliveira et al., 2019).

These ecosystems allow vertical information flows, from competitor firms, and horizontal information flows, from customer or supplier firms (Lacam, 2020), and thus significantly enrich the company's relational capital.

4. Challenges:

The previous discussions regarding the transformation of IC through big data brings us to reflect on the challenges that this poses in the organisation. These challenges should be adequately managed for a successful association between big data and IC. Indeed, as stated by Busso et al. (2021), the analyses presented in the literature, seeking to link IC and big data, are fundamentally based on how big data is managed and incorporated into this capital.

Erevelles et al. (2016) argue that the inability to take advantage of big data is often due to its particular resource requirements. Among the most prominent challenges faced by businesses are technical management challenges in storing, processing, and analysing massive data (Jony et al., 2016; Katal et al., 2013). In addition to security issues, which concern both the media on which the data is stored and the structure and content of the data itself. As explained by Abraham et al. (2023), it involves ensuring the preservation of security requirements related to accessibility, authenticity, availability, confidentiality, integrity, and reliability of the data.

Specific requirements exist for personal data, particularly that relating to human resources. In such cases, companies must ensure that they comply with prevailing regulations, concerning restrictions on collection and use, transparency in data processing, clarity regarding the purposes of collection, etc. (Carl, 2021).

Similarly, there are technical complexity problems (Jony et al., 2016) concerning the veracity and reliability of data sources (Wirén et al., 2019) and the quality of the data itself (Fleckenstein & Fellows, 2018). Data quality, as stated by Wang and Strong (1996), must meet four attribute categories: i) intrinsic data quality, which includes the objectivity, accuracy and credibility of the data; ii) contextual quality, which refers to the relevance, completeness and latency of the data; iii) representational quality, which refers to the format and interpretability of the data; iv) accessibility quality, which refers to the possibility of accessing the data and its security. Problems of scalability and heterogeneity are also posed by the volume and variety of data (Katal et al., 2013), in addition to the existence of fragmented data appearing in the form of silos dispersed across the enterprise (Fleckenstein & Fellows, 2018).

Finally, the incorporation of big data into IC introduces also managerial complexity, particularly in terms of integrating the technology and the necessary skills combining technical and business expertise (McAfee & Brynjolfsson, 2012), defining governance structures and mechanisms, through the allocation of rights and duties linked to decision-making (Khatri & Brown, 2010), and establishing a data-driven culture, considered by Anderson (2015) to be a decisive element in the integration of big data.

Conclusion:

In a business environment where change is the only constant variable (Senge, 1990, as cited in Bontis, 1999), big data is of growing strategic interest and is becoming omnipresent in organisations. A presence that inevitably interacts with the existing resources within them.

In line with the fifth phase of research on IC (Harlow, 2018), this paper has attempted to explore the transformative impact of big data on various dimensions of a company's IC. Since data forms the foundation of knowledge, big data exerts a positive influence on this capital. But its unique characteristics necessitate special attention.

In terms of human capital, big data significantly influences selection and retention by aiding in the identification of profiles that companies should recruit or retain, based on collected data. Moreover, it enhances the skills and experiences that constitute human capital, fostering learning, workforce productivity, and efficiency.

Regarding structural capital, the impact of big data is substantial, it enables a flexible information infrastructure, enhances transparency and fluidity of information flows, integrates data from different departments, optimises processes and decision-making, and formalises individual knowledge.

Lastly, concerning relational capital, big data helps to strengthen the company's knowledge of consumers and fosters collaboration with its partners. Nonetheless, it is essential to acknowledge that this integration of big data and interaction resulting with intangible resources present challenges. Therefore, addressing security, technical complexity, and managerial challenges is crucial for successfully implementing and harnessing the full potential of big data. These issues should be explored in greater depth, both practically and academically, in order to help organisations thrive in the digital age, especially given current technological advances in artificial intelligence.

Bibliography list:

Abraham, R., Schneider, J., & vom Brocke, J. (2023). A taxonomy of data governance decision domains in data marketplaces. *Electronic Markets*, 33(22). <https://doi.org/10.1007/s12525-023-00631-w>

Anderson, C. (2015). *Creating a Data-Driven Organization*. O'Reilly. United States of America

Arrow, K. J. (1962). The economic implications of learning by doing. *The Review of Economic Studies*, 29(3), 155–173. <https://doi.org/10.2307/2295952>

Becker, M. C. (2004). The concept of routines twenty years after Nelson and Winter (1982): A review of the literature. In *Industrial and Corporate Change: Vol. DRUID Work*.

Bellinger, G., Castro, D., & Mills, A. (2004). *Data, Information, Knowledge, and Wisdom*.

Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. (2013). *Digital Business Strategy: Toward a Next Generation of Insights*. *MIS Quarterly*, 37(2), 471–482.

Bontis, N. (1998). *Intellectual capital: an exploratory study that develops measures and models*. *Management Decision*, 36(2), 63–76. <https://doi.org/10.1108/00251749810204142>

Bontis, N. (1999). *Managing organizational knowledge by diagnosing intellectual capital: Framing and advancing the state of the field*. *International Journal of Technology Management*, 18(5), 433–462. <https://doi.org/10.1504/ijtm.1999.002780>

Bontis, N. (2001). *Assessing knowledge assets: A review of the models used to measure intellectual capital*. *International Journal of Management Reviews*, 3(1), 41–60. <https://doi.org/10.1111/1468-2370.00053>

Boyd, D., & Crawford, K. (2012). *Critical questions for big data: Provocations for a cultural, technological, and scholarly phenomenon*. *Information, Communication and Society*, 15(5), 662–679. <https://doi.org/10.1080/1369118X.2012.678878>

Brown, B., Chui, M., & Manyika, J. (2011). *Are you ready for the era of “big data”?* *McKinsey Quarterly*, 4, 24–35.

Busso, D., Di Berardino, D., & Tonelli, A. (2021). *The Debate on IC, Smart Technologies, and Digitalization*. In M. S. Chiuccuhi, R. Lombardi, & D. Mancini (Eds.), *Intellectual Capital, Smart Technologies and Digitalization (SIDREA Ser)*. Springer, Cham. https://doi.org/10.1007/978-3-030-80737-5_1

Carl, K. V. (2021). *Corporate Digital Responsibility: Evaluating Privacy and Data Security Activities on Company-level*. *Lecture Notes in Informatics (LNI), INFORMATIK*, 757–771.

Carlucci, D., Marr, B., & Schiuma, G. (2004). *The knowledge value chain: How intellectual capital impacts on business performance*. *International Journal of Technology Management*, 27(6–7), 575–590. <https://doi.org/10.1504/IJTM.2004.004903>

Ciuriak, D. (2019). *Unpacking the Valuation of Data in the Data-Driven Economy*. *SSRN Electronic Journal*, April, 26–27. <https://doi.org/10.2139/ssrn.3379133>

Comuzzi, M., & Patel, A. (2016). *How organisations leverage Big Data: A maturity model*. In *Industrial Management & Data Systems* (Vol. 116, Issue 8). <https://doi.org/10.1108/IMDS-12-2015-0495>

Coyle, D., Diepeveen, S., Wdowin, J., Kay, L., & Tennison, J. (2020). *The Value of Data Policy Implications*. In *Bennett Institute for Public Policy, Cambridge and the Open Data Institute*.

Curry, E. (2016). *The Big Data Value Chain: Definitions, Concepts, and Theoretical Approaches*. In J. M. Cavanillas, E. Curry, & W. Wahlster (Eds.), *New horizons for a data-driven economy: a roadmap for usage and exploitation of big data in Europe*. Springer Nature. <https://doi.org/10.1007/978-3-319-21569-3>

Davenport, T. H., Barth, P., & Bean, R. (2012). *How "Big Data" is Different*. MIT Sloan Management Review, 54(1).

De Mauro, A., Greco, M., & Grimaldi, M. (2015). *What is big data? A consensual definition and a review of key research topics*. AIP Conference Proceedings, 1644, 97–104. <https://doi.org/10.1063/1.4907823>

De Santis, F., & Presti, C. (2018). *The relationship between intellectual capital and big data: a review*. Meditari Accountancy Research, 26(3), 361–380. <https://doi.org/10.1108/MEDAR-10-2017-0222>

Dumay, J. (2016). *A critical reflection on the future of intellectual capital: from reporting to disclosure*. Journal of Intellectual Capital, 17(1), 168–184. <https://doi.org/10.1108/JIC-08-2015-0072>

Edvinsson, L., & Sullivan, P. (1996). *Developing a Model for Managing Intellectual Capital*. European Management Journal, 14(4), 356–364. [https://doi.org/10.1016/0263-2373\(96\)00022-9](https://doi.org/10.1016/0263-2373(96)00022-9)

Erevelles, S., Fukawa, N., & Swayne, L. (2016). *Big Data consumer analytics and the transformation of marketing*. Journal of Business Research, 69(2), 897–904. <https://doi.org/10.1016/j.jbusres.2015.07.001>

Erickson, S., & Rothberg, H. (2014). *Big data and knowledge management: Establishing a conceptual foundation*. The Electric Journal of Knowledge Management, 12(2), 108–116.

Erickson, S., & Rothberg, H. (2018). *Big data et Knowledge management pour établir des fondations conceptuelles*. Les Cahiers Du Numérique, 14(1), 63–82. <https://doi.org/10.3166/lcn.14.1.63-82>

Fleckenstein, M., & Fellows, L. (2018). *Implementing a Data Strategy*. In *Modern Data Strategy* (pp. 35–54). Springer International Publishing. <https://doi.org/10.1007/978-3-319-68993-7>

Garavan, T. N., Morley, M., Gunnigle, P., & Collins, E. (2001). *Human capital accumulation: The role of human resource development*. Journal of European Industrial Training, 25(2/3/4), 48–68. <https://doi.org/10.1108/EUM0000000005437>

Garcia-Arroyo, J., & Osca, A. (2021). *Big data contributions to human resource management: a systematic review*. *International Journal of Human Resource Management*, 32(20), 4337–4362. <https://doi.org/10.1080/09585192.2019.1674357>

Gelhaar, J., Groß, T., & Otto, B. (2021). *A taxonomy for data ecosystems*. *Proceedings of 54th Hawaii International Conference on System Sciences*, 6113–6122. <https://doi.org/10.24251/hicss.2021.739>

Grant, R. M. (1996). *Toward a Knowledge-Based Theory of the Firm*. *Strategic Management Journal*, 17, 109–122.

Guthrie, J., Ricceri, F., & Dumay, J. (2012). *Reflections and projections: A decade of Intellectual Capital Accounting Research*. *British Accounting Review*, 44, 68–82. <https://doi.org/10.1016/j.bar.2012.03.004>

Hamilton, R. H., & Sodeman, W. A. (2020). *The questions we ask: Opportunities and challenges for using big data analytics to strategically manage human capital resources*. *Business Horizons*, 63, 85–95. <https://doi.org/10.1016/j.bushor.2019.10.001>

Harlow, H. D. (2018). *Developing a knowledge management strategy for data analytics and intellectual capital*. *Meditari Accountancy Research*, 26(3), 400–419. <https://doi.org/10.1108/MEDAR-09-2017-0217>

Hilbert, M. (2016). *Big Data for Development: A Review of Promises and Challenges*. *Development Policy Review*, 34(1), 135–174. <https://doi.org/10.1111/dpr.12142>

Hupperz, M., Möller, F., Gür, I., & Otto, B. (2021). *What is a Data-Driven Organization ?* Twenty-Seventh Americas Conference on Information Systems, May.

Hussain, A., Nisar, Q. A., Khan, W., Niazi, U. I., & Malik, M. (2023). *When and how big data analytics and work practices impact on financial performance: an intellectual capital perspective from banking industry*. *Kybernetes*. <https://doi.org/10.1108/K-11-2022-1623>

Jones, C. I., & Tonetti, C. (2020). *Nonrivalry and the Economics of Data*. *American Economic Review*, 110(9), 2819–2858. <https://doi.org/10.1257/aer.20191330>

Jony, R. I., Rony, R. I., Rahat, A., & Rahman, M. (2016). *Big Data Characteristics, Value Chain and Challenges*. *Proceedings of the 1st International Conference on Advanced Information and Communication Technology*, 1–6.

Kabir, N., & Carayannis, E. (2013). *Big data, tacit knowledge and organizational competitiveness*. *Journal of Intelligence Studies in Business*, 3, 54–62. <https://doi.org/10.37380/jisib.v3i3.76>

Kaiser, C., Festl, A., Pucher, G., Fellmann, M., & Stocker, A. (2019). *The vehicle data value chain as a lightweight model to describe digital vehicle services*. *WEBIST 2019 - Proceedings of the 15th International Conference on Web Information Systems and Technologies*, 68–79. <https://doi.org/10.5220/0008113200680079>

Katal, A., Wazid, M., & Goudar, R. H. (2013). *Big Data: Issues, Challenges, Tools and Good Practices*. *Sixth International Conference on Contemporary Computing (IC3)*, 404–409.

Khatri, V., & Brown, C. V. (2010). *Designing data governance*. *Communications of the ACM*, 53(1), 148–152. <https://doi.org/10.1145/1629175.1629210>

Kitchin, R. (2014). *The data revolution: Big data, open data, data infrastructures and their consequences*. SAGE. <https://doi.org/10.29085/9781783304752.021>

La Torre, M., Botes, V. L., Dumay, J., Rea, M. A., & Odendaal, E. (2018). *The fall and rise of intellectual capital accounting: new prospects from the Big Data revolution*. *Meditari Accountancy Research*, 26(3), 381–399. <https://doi.org/10.1108/MEDAR-05-2018-0344>

Lacam, J. (2020). *Data: A collaborative ?* *Journal of High Technology Management Research*, 31(100370). <https://doi.org/10.1016/j.hitech.2020.100370>

Macfeely, S. (2020). *In search of the data revolution: Has the official statistics paradigm shifted?* *Statistical Journal of the IAOS*, 36(4), 1075–1094. <https://doi.org/10.3233/SJI-200662>

Mayer-Schönberger, V., & Cukier, K. (2013). *Big Data: A Revolution that Will Transform how We Live, Work, and Think*. Houghton Mifflin Harcourt.

McAfee, A., & Brynjolfsson, E. (2012). *Big data: The Management Revolution*. *Harvard Business Review*, 90(10), 61–67. <https://doi.org/10.4324/9780367821814-27>

Merendino, A., Dibb, S., Meadows, M., Quinn, L., Wilson, D., Simkin, L., & Canhoto, A. (2018). *Big data, big decisions: The impact of big data on board level decision-making*. *Journal of Business Research*, 93, 67–78. <https://doi.org/10.1016/j.jbusres.2018.08.029>

Miele, S., & Shockley, R. (2013). *Analytics: The real-world use of big data*.

Miller, H. G., & Mork, P. (2013). *From data to decisions: A value chain for big data*. *IT Professional*, 15(1), 57–59. <https://doi.org/10.1109/MITP.2013.11>

Nahapiet, J., & Ghoshal, S. (1998). *Social capital, intellectual capital, and the organizational advantage*. *The Academy of Management Review*, 23(2), 242–266. <https://doi.org/10.2307/259373>

Oliveira, M. I. S., Barros Lima, G. D. F., & Farias Lóscio, B. (2019). *Investigations into Data Ecosystems : a systematic mapping study*. *Knowledge and Information Systems*, 61, 589–630. <https://doi.org/10.1007/s10115-018-1323-6>

Pauleen, D. J., & Wang, W. Y. C. (2017). *Does big data mean big knowledge? KM perspectives on big data and analytics*. *Journal of Knowledge Management*, 21(1), 1–6. <https://doi.org/10.1108/JKM-08-2016-0339>

Petty, R., & Guthrie, J. (2000). *Intellectual capital literature review :Measurement, reporting and management*. *Journal of Intellectual Capital*, 1(2), 155–176. <https://doi.org/10.1108/14691930010348731>

Raguseo, E. (2018). *Big data technologies: An empirical investigation on their adoption, benefits and risks for companies*. *International Journal of Information Management*, 38(1), 187–195. <https://doi.org/10.1016/j.ijinfomgt.2017.07.008>

Schumpeter, J. A. (1983). *The Theory of Economic Development An Inquiry into Profits, Capital, Credit, Interest, and the Business Cycle*. Transaction Publishers.

Secundo, G., Del Vecchio, P., Dumay, J., & Passiante, G. (2017). *Intellectual capital in the age of Big Data: establishing a research agenda*. *Journal of Intellectual Capital*, 18(2), 242–261. <https://doi.org/10.1108/JIC-10-2016-0097>

Seleim, A. A. S., & Khalil, O. E. M. (2011). *Understanding the knowledge management-intellectual capital relationship: A two-way analysis*. *Journal of Intellectual Capital*, 12(4), 586–614. <https://doi.org/10.1108/14691931111181742>

Sena, V., & Ozdemir, S. (2020). *Spillover effects of investment in big data analytics in B2B relationships: What is the role of human capital?* *Industrial Marketing Management*, 86, 77–89. <https://doi.org/10.1016/j.indmarman.2019.05.016>

Singh, R., Sharma, P., Foropon, C., & Belal, H. M. (2022). *The role of big data and predictive analytics in the employee retention: a resource-based view*. *International Journal of Manpower*, 43(2), 411–447. <https://doi.org/10.1108/IJM-03-2021-0197>

Teece, D. J. (2000). *Strategies for Managing Knowledge Assets: The Role of Firm Structure and Industrial Context*. *Long Range Planning*, 33, 35–54. [https://doi.org/10.1016/S0024-6301\(99\)00117-X](https://doi.org/10.1016/S0024-6301(99)00117-X)

Veldkamp, L., & Chung, C. (2019). *Data and the Aggregate Economy*. *Journal of Economic Literature*, 1–36.

Wamba, S. F., Akter, S., Edwards, A. J., & Chopin, G. (2014). *How “big data” can make big impact: Findings from a systematic review and a longitudinal case study*. *International Journal of Production Economics*, 165, 234–246. <https://doi.org/10.1016/j.ijpe.2014.12.031>

Wang, R. Y., & Strong, D. M. (1996). *Beyond accuracy: What data quality means to data consumers*. *Journal of Management Information Systems*, 12(4), 5–33. <https://doi.org/10.1080/07421222.1996.11518099>

Wirén, M., Mäntymäki, M., & Islam, A. N. (2019). *Big Data Value Chain : Making Sense of the Challenges*. *18th Conference on E-Business, e-Services and e-Society (I3E)*, 125–137.

Wixom, B. H., & Ross, J. W. (2017). *How to monetize your data*. *MIT Sloan Management Review*, 58(3), 10–13. <https://doi.org/10.7551/mitpress/11633.003.0009>

Zerbino, P., Aloini, D., Dulmin, R., & Mininno, V. (2018). *Big Data-enabled Customer Relationship Management: A holistic approach*. *Information Processing and Management*, 54(5), 818–846. <https://doi.org/10.1016/j.ipm.2017.10.005>