The Role of Data Science in Modern Commerce

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Abstract:

The purpose of the research is to outline the advantages of data science (DS) for businesses, as well as the possibilities and problems associated with growing this capacity. First, a review of the literature was done. Later, 211 informants—the most seasoned managers of medium-sized and big businesses from various economic sectors—responded to a structured electronic interview designed to gather empirical data. The data were then subjected to content analysis. The most commonly noted advantages are as follows: facilitation of opportunity sensing, organizational performance management, data-driven culture development, support for agile data analysis and insight generation, enhanced data quality, and ease of comprehension of the business environment. The following issues have been noted the most: data-driven culture; data governance and strategy; data allocation in analytical technologies; and DS training. Apart from delineating the current state of the art, it advances scientific understanding by identifying and disclosing 11 advantage indicators and 16 difficulty indicators related to analytical capacities. Organizations must endeavour to allow leadership mentality shift, formulate policies and governance structures, allocate resources for information technology, and refresh staff capabilities in order to turn data into information and bring value to the company.

Keywords: Competitive Advantage, Data Science, Analytical Capabilities, Big Data Analytics, Dynamic Capabilities, Business Intelligence Analytics

Introduction

Data is becoming an organization's most important asset, and it may be the only one that is really unique (Nielsen, 2017). Businesses have easy access to vast amounts of data from a range of sources, which can be analyzed quickly and reliably to significantly boost the possibility of obtaining useful insights to inform data-driven decision-making (Chen et al., 2012; Waller and Fawcett, 2013). Researchers and professionals regard data-driven decision-making in this context as a proactive means of bringing value to the company (Chin et al., 2017). According to Rob Roy, chief digital officer of Sprint, "having a data-first mentality is a crucial first step, but then you need to put in place the processes and capabilities to be able to use the data" (Roy and Seitz, 2018) in an interview that was published by the McKinsey Global Institute.

Generally speaking, this is challenging to operationalize in the actual corporate management setting. The challenges are multifaceted and include, for example, integrating data analysis into a corporate strategy vision; agents' limited knowledge and behavior when using analytical tools; developing mechanisms and governance policies and corporate data management; and significant investment in information technology resources, per a study by the McKinsey Global Institute (Chin et al., 2017) and

scientific research (Comuzzi and Patel, 2016; Shamim et al., 2019).

Gaining knowledge and expertise in big data (BD) requires a mental shift that might set one apart from the competition (Barton and Court, 2012). Organizations must use cutting-edge analytical tools and techniques to transform data into information as they incorporate more data into their decision-making process. The multidisciplinary area of data science (DS) investigates the methods for gathering, organizing, and converting data into knowledge and information to facilitate data-driven decision-making (Waller and Fawcett, 2013). Within the realm of business, data science is referred to as business intelligence and analytics (BI&A) or data science for business (DSB), which includes both big data analytics (BDA) and business data (BD) (Newman et al., 2016). To provide managers advice and insights, DSB facilitates the gathering, organizing, analyzing, and visualizing of vast volumes of data (Chen et al., 2012; Waller and Fawcett, 2013).

A pertinent challenge for organizations is the development of analysts' and decisionmakers' favorable analytical skills, dependable organizational procedures for gathering and organizing vast amounts of data, and management structures that support BD analysis and value creation through the production of actionable insights. Successful businesses like Amazon, Google, Alibaba, Netflix, and Spotify were created to investigate BD (Hagiu and Wright, 2020). To identify practical possibilities and problems, further study is needed before applying DSB in enterprises, financial institutions, and educational institutions whose services and products were not initially organized on BD. The study by Carillo (2017) demonstrated this research gap, and more recent findings support the need for empirical studies on the effects of implementing DS and BD techniques in businesses (Grover et al., 2018). Our study's objective is to determine the advantages of DSB for enhancing decision-making and adding value for businesses by emphasizing the crucial elements, difficulties, and possibilities associated with growing this skill. The subject is important because businesses may achieve better performance by using their business operations data to inform choices made via BDA and DS (Brynjolfsson et al., 2011; Müller et al., 2018).

Literature review

According to Chen et al. (2012), the phrase BI&A refers to technologies, methodologies, and enhanced storage applications, management, and data visualization to aid in decision-making. As per Newman et al. (2016), firms who are using the BI&A methodology now consider the capacity to manage DS to be a critical business liability. According to Waller and Fawcett (2013), BI&A is synonymous with DSB, and it includes the ideas of BD and BDA (Newman et al., 2016). Furthermore, whilst the term BI&A is more often used in business, the word DSB is more widely used in academics and among practitioners from a variety of areas. The multidisciplinary area of data science (DS) examines how to interpret data and turn it into knowledge and information. Since decision-making is often of utmost importance to the company, it may be used broadly to all functional areas of business with the aim of enhancing decision-making (Newman et al., 2016; Waller and Fawcett, 2013).

Data science for business benefits

Businesses that use DS and BD technology may increase productivity by 5–6% (Brynjolfsson et al., 2011). In a more recent study, Müller et al. (2018) examined data from 814 businesses from 2008 to

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2014 and found that investments in BD and DS are linked to a 3–7% increase in corporate productivity. Furthermore, Troilo et al. (2016) examined professional sports companies and contrasted the increase attained by these organizations (7.2%) in the year after their adoption with the industry's predicted growth of 3%. Teo et al. (2016) found that compared to other firms, those who announce the deployment of BA have higher favorable stock market responses.

Wimmer and Aasheim (2017) suggest that the perceived value of distributed sensing (DS) is contingent upon a number of factors, including information quality, system quality, social norms, and behavioral control. According to Is ik et al. (2013), the effectiveness of analytical projects depends on the quality of the data, user accessibility, and system integration.

Data science for business

The literature claims that the analytical skills and resources enable improved data and sophisticated analytical procedures, suggesting improved information management and identification that helps decision-making and, ultimately, creates value for businesses. **Challenges for developing data science for business**

According to Carillo (2017), data scientists are not the only ones who should be developing their analytical abilities. According to the author, managers need to develop into management scientists with a multidisciplinary skill set that includes business management, analytical and modeling tools and methodologies, knowledge, and data management abilities. A rising number of companies are creating the post of chief data officer, which positions a new generation of leaders to investigate data value, as business strategies become more and more dependent on data (Lee et al., 2014).

Finding new talent and training staff in DS skills is another challenge when working with BD. These skills are necessary to identify patterns in massive data sets and convert them into actionable information (Chin et al., 2017; McAfee and Brynjolfsson, 2012).

Furthermore, as Redman (2013) notes, poor data quality has a significant impact on BDA as managers would rapidly discount it and rely on their gut feelings when making judgments. Finding, gathering, and integrating data via functional silos both within and outside the company provide additional challenges (Kitchens et al., 2018). According to Frisk and Bannister (2017), managers must alter the culture of decision-making in order to accomplish the dramatic performance increases that may be attained by skillfully using data.

We were able to get a deeper grasp of various advantages related to the use of DS in business thanks to the literature research. The major obstacles to this capacity's development, as documented in the literature, were also identified and arranged with help from the literature study. Nevertheless, we discovered that the available empirical information is few and based on a variety of theoretical and empirical viewpoints, which is concerning given the need to learn more about the primary advantages and difficulties experienced by DS users in the business sector. Therefore, this research attempts to identify the perceived advantages of DSB in organizations as well as the chances and difficulties for the development of this analytical ability. It is based on the theoretical consolidation of the state of the art of DSB and the ideas and categories we systematized. As a result, we developed the following research inquiries:

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RQ1. What advantages does DSB provide businesses?

RQ2. What obstacles must DSB development overcome?

Research methodology

Two phases went into the development of our qualitative research. First, a subjective narrative was used to perform a literature analysis in order to collect the findings of the analyzed studies, describe the key ideas, and illustrate the discussion agenda in the state of the art of research on the issue (Paré et al., 2015). Finding the theoretical underpinnings and research topics that would organize the chosen coding system was the aim of the conceptual stage. Data were then gathered using an electronic interview that was constructed in order to capture a variety of perspectives, and they were then subjected to content analysis. The purpose of this empirical step was to examine data on DSB users' perceptions. We adhered to the project validity, analytical validity, and inferential validity guidelines proposed by Venkatesh et al. (2013) in order to ensure the validity of our qualitative study. Comments on these validity checks are made in the following subsections.

Design of the survey instrument and selection of informants

The design of the research instrument was informed by theoretical insights and research inquiries. In order to optimize research reliability and maintain data stability, the study employs a structured questionnaire with open-ended questions pertinent to research goals.

2018 saw the collection of data using an electronic form. 369 people in all, representing various Brazilian firms and active in professional networks or associations pertaining to IT, data governance, business intelligence, BA, BD, and DS, were asked to complete the questionnaire. A total of 211 replies were obtained from this group. Informants work in the following sectors: public sector (12%), retail and wholesale trade (6%) and other sectors like energy and media (7%). They are employed by large (45%), medium (31%), and small (24%) organizations that are in the service sector (61%), which includes IT, business management, marketing, and market intelligence as well as financial and banking services. In the industrial sector (14%), which includes automobile, infrastructure, food, electronics, pharmaceutical, and metal-mechanic industries? We guaranteed the project validity of our research by keeping a strict screening process for informants and providing them with avenues to express their opinions (Venkatesh et al., 2013).

Data analysis procedures

In order to establish a connection between the research ideas found in the literature study and the data collected, their categories, and settings discovered via qualitative research, our content analysis was conducted (Bardin, 2009; Creswell and Creswell, 2018). The combination of theoretical components and practical data produced the coding system. Procedures for open, axial, and selective coding were used (Corbin and Strauss, 2015). Following data coding, information was classified and grouped based on predetermined criteria as part of the categorization process (Bardin, 2009). The categories (dimensions) derived from the literature review and the subcategories (indicators) based on the research question classification that arose from the empirical data are shown in Figure 3 below.

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Software from QSR NVivo v11 VR was used to assist data analysis methods. At each stage of the data analysis process, the researchers confirmed the inferential validity through the rigor in the analysis and data interpretation (Venkatesh et al., 2013), which raises the reliability of the research (Creswell and Creswell, 2018), and the analytical validity by establishing and carrying out the data collection and analysis procedures rigorously in the application of the methods so that the findings are reliable, consistent, and plausible.

Results & Discussion

Descriptive analysis of informants

Out of the 369 people that were invited, 211 (or 57% of them) turned in their responses. Every informant attested to the use of DSB by their companies. Over 75% of those surveyed are between the ages of 26 and 45, have worked in medium-sized or big enterprises for more least 6 years, and often utilize DSB. The informants' profiles are included in Table I. Over 72% of the population has a post-graduate degree. A degree in business administration, information technology, or statistics is held by around 75% of participants. Over 70% function as intermediate analysts and supervisors, while 25% hold hierarchical positions at the strategic level. The bulk of responders (61%) work for companies in the service industry, which includes information technology (18%), business management (18%), marketing and market research (18%), and banking and financial services (11%).

Benefits realized by users of data science for business

Eleven indicators help to identify the advantages of DSB for decision-making. Table II highlights the primary evidence found in the replies and displays the quantity of evidence classified by benefit indicator. Our informants' numbers are shown in parenthesis.

A shift in perspective and the establishment of a data-driven decision culture are two ways that enhancing the quality of data and information might impact indicators of the "data quality" dimension. The outcomes of the research conducted by Redman (2013) and Shamim et al. (2019) are supported by our findings. Consequently, knowledge about the application of DSB is further enhanced by realizing that, in addition to Wimmer and Aasheim (2017), the advantage of data quality may be one of the factors influencing DSB adoption.

The benefits of leveraging big data to make decisions quickly and effectively, as well as the advantages of using analytical models to increase the precision of optimization and predictive analytics, are the indicators of the "analytical intelligence" dimension (Chen et al., 2012; Kitchens et al., 2018; Duan et al., 2018). Other benefits are also linked to the features and capabilities supported by BD.

Indicators pertaining to the "dynamic capabilities" component (Comuzzi and Patel, 2016; Gupta and George, 2016) emphasize the advantages of data sharing, information integration, communication, and collaborative analysis in promoting organizational learning and knowledge development. Furthermore, Roberts et al. (2016) have identified several indicators that highlight the advantages of enhanced opportunity detection and seizing, as well as flexible change implementation, which may result in the organization's expansion and value creation.

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In terms of enhanced productivity and organizational performance, as well as corporate profitability, the indicators of the "competitive advantages" dimension show the advantages of gaining value and enhancing organizational competitiveness via analytical skills. According to earlier empirical research (Brynjolfsson et al., 2011; Müller et al., 2018), using DSB is associated with better peer performance. These findings are consistent with that research.

It is evident from this that the advantages that DSB users most frequently see are as follows: it facilitates understanding of the business environment, opportunity sensing, and organizational performance management; it supports data analysis and insight generation with agility; it aids in the creation of a datadriven culture; and it improves data quality.

Table 1. Profile of the informants

Profile of the Informants	Total of Informants (n = 211)
Age (years) (%)	
25 - 35	41%
36 - 45	34%
46 - 55	13%
> 55	6%
Professional Experience (%)	
1-5 years	9%
6-10 years	31%
11-15 years	23%
> 15 years	34%
Organization Size (%)	
Small	24%
Medium	31%
Large	45%
Economic Segment (%)	
Services	61%
Industry	14%
Government	12%
Trade	6%
Others	7%
DSB Frequency Use (%)	
Rarely	1%
Occasionally	27%
Frequently	4%

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Table II. Evidences of DSB benefits

Number of evidence by indicator/dimension	Examples of evidence mentioned by informants
Data quality	
Helps to create a data-driven culture (24)	Decrease the impact of opinions by focusing on what is factual and quantifiable (I059)
	Creating a fact-based decision culture and eliminating variability in decision-making (I174)
Reduces uncertainty and improves data consistency and reliabi	May give greater consistency and allow greater reliability in what is presented to support decisions (I004)
	Contributes to the reduction of uncertainties in decision-making (I020)
Broadens the management view on BD (7)	Can give you a broader view of the information (I006)
	We are flooded with data. Without technology support for analyzing BD, the holistic look is hampered (I167)
Analytical intelligence	
Provides analysis, evaluation, prediction, and optimization supp	Understanding internal behavioral patterns from competitors, customers, and suppliers (I068)
	Assists in decision-making and differentiated insights, as well as reducing operational risk from predictive models. In addition, it is able to optimize processes, increasing profitability (I137)
Speeds data analysis and insight generation (26)	In data organization, information crossovers, quick insights, and drivers of choice (I035)
	Information interpreted at the right time and that generates action (I039)
	Contributes to faster data analysis (I246)
Dynamic capabilities	
Facilitates integration and communication (7)	Deconstructing information silos and creating integrated repositories (I014)
	Facilitates communication between areas, helps find opportunities, and reduces time for discussion on strategies (I276)
Facilitates knowledge generation (6)	Taking advantage of your data by leveraging that data and turning it into knowledge (I131)
	The transformation of information into knowledge should be considered a high-value asset for the company (I275)
Helps in understanding business environments and sensing opp	Facilitates the understanding of the positioning, action, and action of the company, both in the market in which it operates and understanding all market players while avoiding possible dependencies or unidentified threats (I063)
	It can contribute to the real understanding of the business. The knowledge gained enables the design of decision-making that creates advantages for the company (I081)
Competitive advantages	
Helps to identify and prioritize strategic changes (9)	Identifying business-oriented chances of fast form and in real-time (I242)
	It can contribute to preventing, for example, frauds in banking systems using predictive modeling (I303)
	Identifying the critical elements to prioritize decision-making and change actions (I017)
Facilitates management of organizational performance (12)	Use the data collected to create new customer products and/or new attributes (I228)
	Facilitates KPI control by quickly alerting you to any problems or opportunities (I228)
	Facilitates data crossover by broadening managers' view of company performance and market movements (I091)
Improves competitiveness (8)	Measuring and monitoring processes to analyze their effectiveness and possibilities for improvement (I119)
	Those who use these tools properly will always be ahead of the competition (I046)
	It is essential to the success of any company. There is no way to operate in a competitive market without knowing how it behaves, without keeping up with trends and susceptible developments (I209)

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Table III. Evidences of challenges for DSB development

Dimension	Indicator	No. of Evidences by Indicator/Dimension
Leadership and Culture	Data-Driven Decision Culture	48
	Senior Management Sponsorship	7
	Resistance to Change	4
Strategy, Structure, and Processes	Data Governance	8
	Strategy to Get Value from Data	8
	Data Analysis	7
	Data Sharing	7
	Information Architecture	6
	Organizational Structure	5
	Analysis Procedures	5
Talent Management	DS Training	29
	User Engagement	7
	Transformation of Data into Knowledge	5
Information Technology	Investment in Technological Evolution	24
	Artificial Intelligence	6
	Integration and Data Security	4

The challenges and opportunities associated with each dimension are presented and discussed in the following subsections.

Leadership and culture

The answers that were received (59 citations) mostly addressed aspects of the cultural component. According to informant I167, these examples highlight the need of altering the prevailing management cognitive paradigm in order to facilitate data-driven decision-making: "The cultural barrier remains the biggest challenge (our emphasis)." It is noteworthy that some managers continue to make judgments solely primarily on instinct (our emphasis). Concerning the difficulty in persuading senior management that choices should be made on the basis of facts rather than "feelings," which is one of the main issues we argue about these days, as well as the difficulty in including top executives and dealing with opposition to change: (I 272).

Research suggests that companies should pay close attention to how a data-driven culture is developed, guided by an executive body dominant mindset that takes into account using analytical results to qualify the strategic vision and decision-making processes effectively, as suggested by Duan et al. (2018), Gupta and George (2016), McAfee and Brynjolfsson (2012), and Shamim et al. (2019).

Strategy, structure and processes

According to the responses, this dimension was the second most represented (46 citations). We draw attention to the references to organizational management structures, policy development, data lifecycle management, analytical techniques, information integration into panels, and the conversion of data into knowledge. Some of these components are shown by the answers that follow: "In addition to the clearly defined objectives to identify useful data [our emphasis], it is necessary to have defined procedures and appropriate tools." (I029); "total integration of organization data into a collaborative environment [our emphasis] and that allows the production of ad hoc analysis" (I266); and "[...] it is essential to have a well-organized structure for the company's data flow." (I111).

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These issues center on the need of setting up the best corporate data governance and management model and developing a corporate data strategy in order to support value creation processes (Comuzzi and Patel, 2016; Frisk and Bannister, 2017; Grover et al., 2018; Nielsen, 2017).

Talent management

The human factor is covered in 41 citations. These cite the informant I227's assertion that "companies should invest more in training to enable their professionals, making them qualified to perform more efficient and effective data analysis, generating insights that add value to the organization [our emphasis]" and emphasize the need for managers and analysts to receive training in intelligence methods and data analysis. Teams need these complementary abilities and talents in order to extract value from the data: People are the most important factor [our emphasis], and in order to exploit the data's hidden treasure, new team formations with complementing traits distinct from those of prior teams are required (I283). Exploring the value that data may bring requires limiting agents' knowledge and conduct while using analytical tools (Lee et al., 2014; Merendino et al., 2018). Furthermore, new specialized positions in data science, modeling, analysis, translation, management, and governance—such as chief data officer, data scientist, and managementscientist— are emerging in the organizational field. As a result, companies must be prepared to attract and utilize this workforce and develop training plans (Carillo, 2017; Chin et al., 2017; Grover et al., 2018; Lee et al., 2014).

Information technology

In the technology dimension, 34 citations were found that emphasize the importance of promoting investments in the development of information technologies that assist DSB, such as BD and artificial intelligence. This worldview is best represented by the following answers: "big data analytics is the big challenge in identifying trends and patterns of behavior in the marketplace [our emphasis]" (I002). "Using machine learning techniques to automate manual work" (I219). "I believe that incorporating Artificial Intelligence into the analysis of already qualified data can greatly increase the assertiveness of decision-making" [our special emphasis] (I288). In fact, an intensive investment in information and information technology resources and assets is required for the development, adoption, maintenance, and continuous improvement of more sophisticated analytical technologies (Comuzzi and Patel, 2016; Grover et al., 2018), so, while less frequently mentioned in reports, this dimension is no less important than the others.

Finally, the following response offers a holistic perspective of the issues in these several aspects, as suggested by Gupta and George (2016), Müller and Jensen (2017), and Vidgen et al. (2017): The outcome can only be realized if the organization's people and culture are focused on information management, analysis, and utilization [our emphasis]. Furthermore, meaningful changes will not occur unless decision-makers commit and participate. Technology must be viewed as a tool rather than an end in itself; people are the elements that make a difference; no amount of technology is worth anything unless people are empowered, interested, familiar, and have a strong culture focused on production and knowledge application (intelligence), with finality and purpose [our emphasis] (I197). This citation effectively summarizes the content analysis and explanation of the findings.

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Thus, the following final comments highlight the implications and contributions of our work.

Conclusion

This research looked at the potential and difficulties that come with developing this skill as well as the advantages that businesses may get from using DSB. 211 informants' responses were examined, adding pertinent empirical data. We combined several perspectives on the advantages and difficulties to create three theoretical contributions. There are also research possibilities and management guidelines for upcoming investigations provided. Contributions from the theory The first contribution focuses on mapping the current state of the art in DSB research in order to compile and summarize the advantages and difficulties mentioned in the literature. The second and third contributions pertain to the advancement of scientific knowledge, grounded in empirical evidence, by means of a descriptive synthesis of 11 benefit indicators linked to the utilization of DSB. Of these, the most significant are those that enable agile data analysis and insight generation, foster a culture of data-driven innovation, enhance data quality, facilitate comprehension of the business environment, and support opportunity sensing and organizational performance management. A total of sixteen problems were found, with data-driven culture, data governance and strategy, DS training, and investment allocation in analytical technology ranking as the most crucial. Implications for management and information Our study's findings advance understanding of and qualification for strategic information management techniques used by businesses, assisting in the communication of the advantages and difficulties associated with the growth of analytical capacities. By fostering a data-driven culture, developing strategies and governance mechanisms, and updating the knowledge and abilities of analysts, managers, and directors of strategic data management, these contributions address the need for an executive mindset shift. They also emphasize the necessity of allocating resources to information and technology assets in order to investigate the potential value that can be obtained through business analytics. Restrictions and recommendations for further research Lastly, this study is qualitative research that reflects specific viewpoints of respondents in the Brazilian setting, which prohibits the generalization of the results even if the material was gathered from a vast number of informants. Future research might expand on our knowledge of the difficulties associated with data governance and data-driven decision-making in the face of organizational, strategic, and cultural constraints found in this study. Furthermore, in order to comprehend how these new professional profiles might assist enterprises in realizing the value of data, empirical studies involving DS experts are required.

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