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Abstract

PhD Thesis

Big Data Analytics Impact upon Organizational Performance

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Keywords

Big data analytics, big data analytics capability, organizational performance, meta-analysis, strategic management, competitive advantage, resource-based theory, business analytics, value.

Part I. Systematic literature review

Our domain of study is big data analytics from the managerial research point of view. We began this research with the ambition to create a map of the existing state of the knowledge and to record the uncharted territories based on our discoveries. Our first objective is to create a systematic presentation of all the notions of big data analytics. We believe this can have both research implications, as well as managerial implications, as it can be a comprehensive introduction within this domain. A researcher could find definitions, characteristics, classifications, best practices, and so on. A manager responsible for the adoption of big data analytics will be interested to understand specific processes, strategies, and capabilities needed to be developed for this transition to run smoothly and to impact performance. In the second part, we want to move the conversation forward and answer some questions. The most basic question is: does big data analytics impact organizational performance? If yes, which type of big data analytics is the most effective? Elaborating further: upon which type of performance does big data analytics have the biggest impact? And these are just a few of the questions we target.

Delimitation of the topic and research motivation

Big data analytics is enjoying considerable popularity and this trend appears to be growing. It is, no doubt, a technological change led by all the hardware and software breakthroughs. We also like to claim that it is a managerial change, as it impacts how managers decide. Also, its success requires a shift in organizational culture as the implementation needs leadership sponsorship, acquiring the right human capital, and not least, some security and legal concerns. This is why we look at this topic from the management perspective.

However, there is no definite answer to the question of whether or not big data analytics does have a positive impact on organizational performance. For someone new to this topic, the results of the most popular studies might show mixed findings. To add even more confusion, we see that there are clear motivations from both sides to overstate the results. On the one side, we have the practitioners: vendors of big data analytics solutions who are interested to sell their products, the leadership of any type of organization, who want to appear as innovators and better than their competition. On the other side, academia: motivated to appear up to date to the managerial challenges of the current age. Academia is also impacted by the publication bias phenomenon, according to which, studies that display strong significant results have a higher chance to be published. All these examples are clues, that from both sides, there are major incentives to declare big data analytics as to the path to success.

Our research is focused to assess the impact of big data analytics upon organizational performance. And if the conclusion to this topic is a positive one, we will develop further, and determine if this positive outcome can be narrowed down to specific types of big data analytics, or type of performance, and some contexts such as sector, organization size, country or year.

The current state of knowledge

As we mentioned initially, we are interested in studying this topic from the management point of view. So, our motivation is to understand to implications for organizations and particularly for managers.

Thus, we had to act like a manager, and first, we had to improve our understanding of this domain. At its origins, big data analytics evolved from business analytics. Contributors to the knowledge of business analytics and big data analytics are located on both sides, practitioners, and academia. Institutes such as TechAmerica Foundation (2012), UpX Academy (2016), or Gartner (n.d.) affirmed one of the earliest and the widely accepted definitions within the domain. From the academia, we consider as pioneering the work of Davenport and Harris (2007) which established the bases for competing on analytics. Evans (2017) classified business analytics types based on the questions they answer: descriptive, predictive, and prescriptive. What sets apart big data analytics from classical analytics are its characteristics. Three of the most widely accepted ones refer to volume, velocity, and variety (Laney, 2001; Zikopoulos et al., 2012; Chen and Zhang, 2014). To these, other researchers such as Van Rijmenam (2013), Seddon and Currie (2017), and Mikalef et al. (2017) suggested additional characteristics: veracity, value, variability, and visualization.

Within the available literature, we were able to find uses of big data analytics across 19 different sectors, and at all the organizational levels: strategic, functional, and operational. Nonetheless, we had difficulties identifying sources that consider this topic across multiple sectors or organizational levels at once. We wanted to find studies that compare the effect between sectors. The only situation was when the samples of the studies were collected across multiple industries. However, in these instances, the industry did not play a significant role, not more than a demographic within the study. We hope that our inclusive approach will fill a gap within this space.

When it comes to the management perspective, we discovered big data analytics from many classical theories such as resource-based theory (Gupta and George, 2016; Akter et al, 2016), dynamic capability theory (Singh and Singh, 2019; Mikalef et al., 2020), knowledge-based view (Côrte-Real et al., 2017; Ghasemaghaei, 2019), information processing view (Roßmann et al., 2018; Zhu et al., 2018), contingency theory (Cao and Duan, 2017), absorptive capacity view (Wang and Byrd, 2017), organizational learning theory (Ghasemaghaei and Calic, 2019). What these researchers have in common is the understanding that the challenge is not to acquire the right technology, but rather to nurture the right organizational culture and develop big data analytics capabilities. This is why some authors consider big data analytics as “the management revolution” (McAfee and Brynjolfsson, 2012).

Based on the prior findings one central question within our study is the following: can organizations obtain an additional effect on performance by developing a big data analytics capability (BDAC), compared to the ones who just adopt simple uses of big data analytics (BDA)? From our experience, researchers study only one dimension at a time, and they are not compared.

As we established, we aim to study the relationship between big data analytics and performance. For the second part of the relationship, the performance, we identified in the available literature, forms such as financial performance, competitive advantage, operational performance, customer satisfaction/ retention, organizational agility market performance, decision making effectiveness, innovation, supply chain performance, employee development/ satisfaction/ motivation, social/ environmental performance. When testing the relationship, researchers tend to focus usually on one or two performance types at a time. The most popular types of performance being: competitive advantage, financial performance, and supply chain performance. By testing them simultaneously, we hope to identify if the impact differs across these types of performance.

Defining the research objectives

As we already explained big data analytics is an important technological change and it appears to impact management itself. As this change promises to bring a new suite of opportunities, at the same time it is packed with a series of threats, especially due to the uncertainties it brings.

So, we can imagine a very legitimate question from a CEO of a company would be: is it worth the effort? Because of this, our main focus is to test if there is a link between big data analytics use and performance increases.

The general objective of this research is to test the relationship between big data analytics (of any form) and performance (of any type). This is a broad general question from which we will derive some specific questions. But, simply put, we want to see if big data analytics generates positive outcomes. The main methodology we use is the meta-analysis in which we will include all the available empirical studies. For some, this approach will appear too general, or too broad. For these, we have to cite one of the pioneers of the meta-analysis study. Glass (1978) anticipated this controversy by pointing out the analogy of comparing apples and oranges. This is acceptable if our objective is to investigate fruits. Later, Rosenthal (1991) reinforced in a similar metaphorical way, that combining apples and oranges is a desirable thing if our goal is the fruit salad. The meta-analysis is an appropriate study methodology for our research question and objective. First, because our question is very broad, this will allow us to test our hypotheses against many studies. In other words, our study will be very inclusive. And second, as a result of the first point, this inclusivity will enable us to generalize the results. As Borenstein et al. (2009) explained, the objective of a meta-analysis study is seldom to combine the results of identical studies, but rather to expand the question based on these studies and to identify some additional patterns. There was no previous study, to our knowledge, which combined in a single model all multiply types of big data analytics and so many types of performance, across so many countries, sectors, firm sizes, and on such a long timeframe. It is understandable though because for an individual primary study is almost impossible to collect so much data. This is why we believe the most viable solution for this goal is a meta-analysis study.

Theoretical objective:

- Identify the required criteria for business analytics activities to evolve to big data analytics.

- Highlight examples of big data analytics used across all sectors based on the available literature.
- Highlight examples of big data analytics uses at all organizational levels based on the available literature.
- Assess the potential impact of big data analytics upon organizational strategy.
- Identify the necessary resources and skills needed to develop a big data analytics capability.
- Classify the practices of big data analytics.
- Determine the methods used for measuring organizational performance.

Empirical objectives:

- Develop a systematic literature review with all the specific indicators.
- Test the impact of big data analytics upon organizational performance by using the meta-analysis methodology.
- Run subgroup analyses in order to isolate the effect based on specific circumstances and to evaluate the differences among the different scenarios.
- Run meta-regressions based on the available classification criteria: big data analytics type, performance method, firm size, industry, country, year of study.
- Operate quality tests for the included effect sizes in order to: identify outliers, assess between-study heterogeneity and evaluate the potential impact of publication bias.
- Elaborate recommendations for both researchers and managers based on the findings.

As we mentioned in the above objectives, our work aims to become a go-to material for whoever is new to the domain of big data analytics as it can serve as a roadmap. We hope to fulfill this objective through our systematic approach to the literature review. Secondly, based on the empirical results of the meta-analysis, we propose to settle the debate of big data analytics and its impact upon performance. A systematic literature review combined with a meta-analysis has the advantage of objectivity, compared to a literature review, and ensures a higher precision for the results and the ability to generalize (Everitt and Hothorn, 2010). Because of this, we hope that the results of our study will serve as the baseline for field experts when designing new studies. Nevertheless, we hope that the subgroup analyses and the meta-regressions' results will provide a guideline towards the best approach and conditions necessary to implement big data analytics in a manner to maximize the positive outcomes.

The Systematic Literature Review

The reason for our entire research, and implicitly for the systematic review, as part of the case study, is to bring more clarity on the state of the literature at the moment of this work. The domain of big data analytics gained tremendous popularity in the past years, from both sides, the practitioners and the academia. But the context shows that both have specific motivations to present themselves as pioneers in this area of expertise. On the one side, the practitioners want to appear as innovators and early adopters compared to their peers. On the other side, within academia, the fear is to be left behind compared to the practitioners' world. So, we identify here some reasons for biases. Simply put, something might be presented as extraordinary and game-changing when in reality it could be just an incremental change.

Because of this, we believe that a simple literature review could not be enough and it would potentially make us perpetuate the same biases. One explanation for this is that the most popular studies are already the ones that found evidence of the success of big data analytics, while the ones which have more *"discouraging"* results might not achieve the same popularity. To overcome such risks, we believe that a systematic literature review is more appropriate, and the next necessary step is a meta-analysis. We envision that these two approaches will go hand in hand, and the results of the first one will serve as the basis for the second.

Our case study is split into two phases: first, a preamble where we did a systematic literature review, and second, the actual meta-analysis study. The aim of the first part is to grasp a better understanding of the literature and the articles we included in our meta-analysis.

In the following paragraphs, we will define our study's hypotheses, explain the criteria based on which we included the chosen studies in our meta-analysis and the main statistical methods we involved.

A simple definition can be found at Higgins et al. (2019) who say that a systematic literature review is a collection of all the available empirical studies which meet the inclusion criteria with the scope to answer a proposed research question. Similarly, according to Bettany-Saltikov (2016), a systematic literature review is a type of literature review that is focused on one research question, it is run in order to assess and synthesize all the available studies which have empirical evidence on that research question, and finally, generate conclusions based on these findings. Of course, the search and inclusion methodology has to be clear and established in advance. There is a structural summarization which we will notice in our review as well. Meaning that the same standardized parts of data will be extracted from each of the included studies.

As the first part of running a systematic literature review, we need to formulate the research question. For this, we need to locate our study's perspective. We assess from a management point of view a phenomenon that appears to have an important influence within organizations: big data analytics. In accordance, we aim to identify the impact of big data analytics upon organizational performance. So, the main research question is:

- ***What is the impact of big data analytics upon organizational performance?***

From this question we derive second-level questions like:

- What types of big data analytics there are?
- How can we assess performance?
- Through which theories/ frameworks are these elements studied?
- Which are the main methodologies used within the included studies?
- Which are the main findings and conclusions of the studies?
- Which are the implications for managers?
- Which are the implications for research?

In line with the preliminary literature findings, we established a series of hypotheses which we will empirically test based on the meta-analysis study:

H1: *Big data analytics positively impacts performance.*

H1a: *Big data analytics positively impacts financial performance.*

H1b: *Big data analytics positively impacts the competitive advantage.*

H1c: *Big data analytics positively impacts operational performance.*

H1d: *Big data analytics positively impacts customer satisfaction/ retention.*

H1e: *Big data analytics positively impacts organizational agility.*

H1f: *Big data analytics positively impacts market performance.*

H1g: *Big data analytics positively impacts decision-making effectiveness.*

H1h: *Big data analytics positively impacts innovation.*

H1i: *Big data analytics positively impacts supply chain performance.*

H1j: *Big data analytics positively impacts employee development/ satisfaction/ motivation.*

H1k: *Big data analytics positively impacts social/ environmental performance.*

H2: *Big data analytics capability has a superior positive impact on performance compared to big data analytics.*

H2a: *Big data analytics capability has a superior positive impact on financial performance compared to big data analytics.*

H2b: *Big data analytics capability has a superior positive impact on the competitive advantage compared to big data analytics.*

H2c: *Big data analytics capability has a superior positive impact on operational performance compared to big data analytics.*

H2d: *Big data analytics capability has a superior positive impact on customer satisfaction/ retention compared to big data analytics.*

H2e: *Big data analytics capability has a superior positive impact on organizational agility compared to big data analytics.*

H2f: *Big data analytics capability has a superior positive impact on the market performance compared to big data analytics.*

H2g: *Big data analytics capability has a superior positive impact on decision-making effectiveness compared to big data analytics.*

H2h: *Big data analytics capability has a superior positive impact on innovation compared to big data analytics.*

H2i: *Big data analytics capability has a superior positive impact on the supply chain performance compared to big data analytics.*

H2j: *Big data analytics capability has a superior positive impact on employee development/ satisfaction/ motivation compared to big data analytics.*

H2k: *Big data analytics capability has a superior positive impact on social/ environmental performance compared to big data analytics.*

H3: *The firm's size moderates the impact of big data analytics on performance.*

H4: *The country moderates the impact of big data analytics on performance.*

H5: *The sector moderates the impact of big data analytics on performance.*

H6: *The year of the study moderates the impact of big data analytics on performance.*

Part II. Research methodology and data analysis

As we presented in the literature review, in order to test the relationship between big data analytics and organizational performance we created two sets of variables. On one side, the two variables where we make the distinction between big data analytics (BDA) and big data analytics capability (BDAC). On the other side, we have the variables for measuring performance: financial performance (FP), competitive advantage (CA), operational performance (OP), customer satisfaction/ retention (CS), organizational agility (OA), market performance (MP), decision making effectiveness (DME), innovation (IN), supply chain performance (SCP), employee development/ satisfaction/ motivation (ES), social/ environmental performance (SEP). Besides these, we also introduced some moderator variables: firm size (large enterprise – LE, small and medium-sized enterprise – SME), sector (according to Rev, N. A. C. E. 2., 2008), country (based on the countries included in the sample), year of the study (from 2010 to 2020).

For the variables explaining big data analytics and performance, we dedicate the entire chapter 3. The distinction between BDA and BDAC is given by the level of integration of this activity within the organization. Simple uses of big data analytics have been classified as BDA. This can include ad-hoc uses, big data investments announcements, operational uses, etc. In order to be classified as BDAC, we had to see proof of specific resources, managerial and technological skills deployed, a data-driven culture, and increased intensity of organizational learning.

When we started this research, we established the objective to run a meta-analysis in which to include all the empirical articles which are conducted on the relationship between big data analytics and organizational performance in one way or another. As a timeframe, we set the lower limit on 2010, because in our initial search on Web of Knowledge we identified this as the period when the first empirical researches have been published. As for the upper limit, we have the cut-off date on July 2020. This was the last time we updated our search.

As the search criteria, we made a combination of big data analytics keywords on the one hand and performance keywords on the other hand. As the search criteria we combined at least one keyword from each column from table below*:*

Table 1. Searching criteria for studies

Keywords		
big data	performance	empirical
business analytics	competitive advantage	management
	value	

Source: own editing

In total, we received in our query 5614 articles, books, or other types of publications. In *Table 2* we display the number by period:

Table 2. The selection process for the included studies

Period	Number of articles	Title & Abstract filter	Filter by content
2010 - 2014	1000	12	4
2015-2017	1000	58	16
2018	947	174	41
2019	918	141	44
< July 2020	1749	185	15
Total	5614	570	120

Source: own editing

After we collected and decided upon the studies which we included in the meta-analysis, the first step was to extract or calculate the effect sizes. The effect sizes are standardized measures of the size of a studied effect. In our study, we used the **standardized regression coefficient (β)** which is similar to ***Cohen's d.*** *Cohen's d* is a form of a *standardized effect size measurement* and represents the standardized difference between two means (Grace-Martin, 2011; Baguley, 2009).

The types of procedures that we included in our meta-analysis. In short, it consists of the following:

(1) meta-analysis results for all the articles combined.

(2) two separated meta-analyses, where we split our data between the articles where the organizations deployed standard big data analytics (BDA) compared to the situation where they developed a big data analytics capability (BDAC).

(3) meta-regressions where we tested the impact of the following dimensions: a big data analytics capability, the type of performance, the firm size, the country of the study, industry, and the year of the study.

(4) subgroups analyses based on BDAC, per country, and per year.

(5) we tested the between-study heterogeneity: outliers' analysis, influence analysis, and GOSH plot analysis.

(6) we tested for the publication bias: funnel plot, small sample bias, and P curve analysis.

For all these analyses we did use the R software where we used the following libraries: *brms, cluster, cowplot, dmetar, dplyr, esc, factoextra, flexmix, forcats, forcats, fpc, gemtc, ggplot2, ggrepel, ggridges, glue, grDevices, grid, gridExtra, mclust, meta, metafor, metaSEM, mvtnorm, netmeta, osfr, PerformanceAnalytics, reshape2, rjags, semPlot, stats, stringr, tidybayes, tidyverse.*

As for the meta-analysis method, it is obvious that the studies we included are extracted from different populations and under different circumstances. Because of this, we chose the random effects model when estimating our true effect sizes.

Conclusions and personal contributions

Discussion and conclusion

We initiated this research intending to test the impact of big data analytics on organizational performance. The domain of big data analytics appears to enjoy great popularity among the business world as well as among the academic world. It is closely related to IT advancements, such as artificial intelligence, machine learning, and deep learning. All these innovative solutions promise to be the pillars of Industry 4.0, the next industrial revolution. Because of this, it is no wonder that a considerable proportion of business leaders want to appear as part of this movement, if not even the main drivers, especially if we think about the tech companies.

However, there is no general agreement on the actual benefits that such a technology is generating. Of course, the existence of big data analytics creates business opportunities especially for the companies which are specialized in offering such solutions. But our interest was broader, in the way that we wanted to assess the impact across all industries and sectors. Additionally, we wanted to test if developing a big data analytics capability (BDAC) can generate an additional positive impact compared to simple big data analytics (BDA) use.

Theoretical contributions

We created a repository-like literature review, which can be a source of information for researchers and managers alike. In the first chapter, we presented the evolution from business analytics towards big data analytics. We did this mainly based on the characteristics of BDA, especially: *volume*, *velocity*, and *variety*. Big data comes in many forms: text analytics, social media analytics, web analytics, mobile analytics, multimedia analytics (image, audio, video), and data collected by the Internet of Things. A regular BDA process would involve operations with the data such as collection, storage, cleansing analyzing, presenting (visualizing), and decision making (Chen and Zhang, 2014).

One of the contributions to the literature is assembling BDA best practices examples across all sectors. And we did this in a structured way by using the Statistical Classification of Economic Activities in the European Community (Rev, N. A. C. E. 2., 2008). Based on this glossary of classification, we found examples for 19 out of 21 sectors. On top of that, we also present a classification of practices by organizational levels: strategic, functional, and operational.

As our research is looking from a strategic management point of view, we were interested to understand if BDA can lead to a competitive advantage. This is why we brought to attention the big data analytics capability concept. As expected, some researchers propose that the most complicated part is not regarding the technology or the necessary technical skills. It is more about nurturing the proper organizational culture, a so-called data-driven culture. It is vital that managers understand the implications of BDA, and they rely on the insights provided by BDA when making decisions. We argue as well, that in order to develop a big data analytics capability (BDAC), organizations have to maintain *valuable, rare, inimitable, and non-substitutable* resources and skills as per the VRIN approach.

Another contribution to the literature is that we presented the big data analytics concept as seen from the point of view of all the theories and frameworks we could find: resource-based theory, dynamic capability theory, knowledge-based view, information processing view, contingency theory, absorptive capacity view, and organizational learning theory, etc. Also based on the literature review we presented the models based on which an organization can develop a BDAC. This is relevant for our research when we reach the meta-analysis part, where we tested the difference between BDA use and BDAC development. We noticed within the studied literature that this comparison has been omitted. The researchers tested either one of the two dimensions, BDA or BDAC. Our objective was to compare them.

In terms of BDA methodologies, we classified the following forms: *big data analytics capability, data-driven environment, big data investments (announcements), big data resources (knowledge assets), ad-hoc use of big data analytics vs. routine use of big data analytics, customer analytics, internet of things.* When it comes to performance, the measurements methods are the following: *financial performance, competitive advantage, operational performance, customer satisfaction/ retention, organizational agility, market performance, decision-making effectiveness, innovation, supply chain performance, employee development/ satisfaction/ motivation, social/ environmental performance.*

When testing the relationship between BDA and performance we narrowed the classification for big data analytics to (1) BDA and (2) BDAC. The reason for this is to gain some statistical power because the clusters would have more effect sizes. In what concerns the performance part, we kept all the 11 methods from the classification.

We identified when reviewing the literature and assessing the included studies in the meta-analysis, the tendency for researchers to focus on one dimension from the BDA spectrum and usually one, with few exceptions, two or three effects of performance. The same approach was used when speaking about the industry in which the study was conducted. Either the sample included mixed sectors, then this detail did not have an important purpose, or the study has been focused on only one sector. By including all the available sectors in our study, and comparing their results, we achieved the possibility to generalize. This is one feature available when doing a meta-analysis.

Empirical contributions

Our main objective was the test the impact of big data analytics upon firm performance and determine if a big data analytics capability will generate a superior positive impact on performance compared to big data analytics.

When we reviewed the literature, we understood that there is an increasing interest in this topic. This has been proved by the numerous studies we found based on our search criteria. As we have shown, we found initially 5614 studies, and after we filtered based on all the inclusion criteria, we kept for our meta-analysis 120 articles.

However, as we highlighted, the studies focused either on BDA or BDAC and only on a few performance dimensions at the time, for example, FP & OP by Abusweilem and Abualoush (2019); FP, OP, IN, & SEP by Akhtar et al. (2019), etc. This limitation appears also when it comes to the other dimensions we reviewed for our model, they are not treated comparatively. Some studies are focused on SMEs or on large enterprises separately, or some studies have a mixed sample, and in this case, the firm size is just a demographic. Similarly for the sector, the researchers do not compare the results across sectors. We believe our approach with the use of the meta-analysis is suitable to cover this gap. We proposed to compare the results based on these moderator variables.

In other words, we wanted to assess the effect of BDA on firm performance, after this, if the BDAC has a superior effect compared to BDA, and if the firm size, the sector, the country, and the year of the study moderate these relationships. Besides this, we also tested separately the impact of BDA and BDAC on each of the 11 types of performance from our model.

The positive effect of BDA on performance has been confirmed as well as the superior benefits of BDAC. Overall, it appears that BDAC produces a higher effect with 70.5% compared to BDA. When we tested separately on the 11 dimensions of performance, the effects indicated in the same positive direction with two exceptions. First, the impact of BDA on DME has not been confirmed. However, BDAC has a strong positive impact on DME. We see two possibilities for which the effect of BDA on DME is not statistically significant. First, it could be a matter of low statistical power, because we had only three observations for this relationship. However, among these three effect sizes, the results are mixed. In the study by Cao et al. (2019)a we have two effect sizes, one positive ($\beta = 0.191$) assessing the impact of BDA on rational DME, and one negative ($\beta = -0.265$), assessing the impact of BDA on intuitive DME. This is in line with our assumption, and with the findings from the literature. The proposal is that data-driven decision-making promises to be a better replacement for decisions based on intuitions or opinions. The other observation is from Wang and Byrd (2017) and here the effect is a strongly positive one ($\beta = 0.441$).

Second, while BDA does have a positive effect on MP, it appears that the additional impact of BDAC on MP is not statistically significant. For this relationship, we cannot say that we lacked statistical power, as there were 22 effect sizes involved. So, it appears that the additional impact ensured by BDAC is not strong enough. Nevertheless, we have to admit that the effect of BDA on MP is the second-highest effect of BDA on some type of performance. We can conclude here that the effect of BDA on MP is already so high that developing a BDAC would not make a difference.

The effects of two moderator variables, firm size and country were not statistically significant. As for the impact of the sector, out of the 19 sectors from which we selected our studies, only 6 appear to have statistically significant added effects. First, on the cluster from the mining and quarrying sector, it appears that the added effect is 0.5676, the main areas being: IN, SCP, and ED (Bag et al., 2020). For the manufacturing sector, the added effect appears to be lower (0.1085). Still, this needs to be interpreted as an additional effect starting from the baseline of 0.3387. For the electricity, gas, steam and air conditioning supply sector the additional effect is negative (-1.2505). Another sector for which the added effect is significantly negative is the constructions sector (-0.6822). For two other sectors, we have statistically stronger additional effects: human health and social work activities (0.4281), especially on SCP (Shokouhyar et al., 2020) and arts, entertainment and recreation (2.8352) where the added effect is mainly on CA (Sjusdal and Lunde, 2019).

Lastly, we would like to address our results in comparison with the results of other studies. Given the methodology of the meta-analysis, we are in a totally and utterly special situation, because by definition a meta-analysis is based on all the works available within the domain. We are confident that our results are as representative as possible for the overall picture. To ensure this, we run several analyses such as between-study heterogeneity (outliers' identification, influence analysis, gosh plot analysis) and we looked for evidence of publication bias (funnel plot analysis and P curve analysis). The results of these analyses led us to believe that indeed the results of our study are in line, and more than this are representative for the existent body of work within this domain.

Managerial implications

It is a legitimate question: what are the implications for practice that we can formulate based on our research, and especially what can be perceived as valuable for managers?

We hope that the current work can serve the practitioners at least on two levels. First, as an introduction to the world of big data analytics, based on the comprehensive literature review we encapsulate. Second, the empirical findings obtained through the meta-analysis can function as encouragement and for setting the right expectations.

We believe our literature review part can serve as a roadmap for someone new to this topic. It is a vast domain and can seem confusing at the beginning for the untrained. We wanted to bring clarity and present both theoretical concepts and practical examples of big data analytics. This included the following: the history of business analytics and evolution towards big data analytics, definitions of big data analytics, characteristics, types of big data analytics, and examples of best practices across all sectors.

Our empirical findings are encouraging and enable us to elaborate some advice for managers. After running a meta-analysis on 120 studies, within ten years timeframe (2010 – 2020), on the topic of big data analytics and organizational performance we can conclude the following:

(1) Big data analytics does indeed have a positive effect on organizational performance. To adopt big data analytics, organizations need the right technological infrastructure, in terms of both, hardware and software. This is needed in order to be able to capture and process the data. Together with these resources, they also need to attract employees with an analytical skillset. Generally, they are called *"data scientists"* and their typical expertise is a combination of programming and statistics. On top of these, they need good domain knowledge as well as the ability to communicate and present data insights as comprehensible information and knowledge. They usually do this with the help of visualization and storytelling.

(2) The effect of big data analytics on performance is enhanced further by 70.5% if the organization manages to develop a big data analytics capability. In the above paragraph, we

discussed the minimum requirements necessary for adopting big data analytics. Now we will summarize the implications for developing a big data analytics capability.

A critical effect is played by the involvement of the leadership in driving this initiative, by sponsoring the deployment and understanding the implications of big data analytics. Leadership has a major impact on the organizational culture. They should aim towards nurturing an organizational learning culture and encourage data-driven decision-making. The power of example is important, they should ground their decision on data insights.

(3) Developing a big data analytics capability can generate a sustainable competitive advantage. Being able to capture, store, analyze, interpret and act on the right data satisfies the criteria of the VRIN framework. If treated properly, data insights are *valuable*. Although the data available is growing at an exponential pace, having the capability to do all the steps to generate the insights combined with a data-driven culture is *rare*. Because it is a mixture of management, technological, and talent capabilities, all acting in a synergetic way, this capability is difficult to be *imitated*. Acquiring the right volume of data can take time, which can act as a barrier for new entrants. Not least, we believe that the other alternative to data-driven decision-making is the decision based on opinions or higher ranks. Thus, we argue that a big data analytics capability is *non-substitutable*.

(4) The types of performance on which simple use of big data analytics (BDA) has the highest impact are the following: financial performance (FP), operational performance (OP), market performance/ sales (MP), and social/ environmental performance (SEP). On these types, the additional impact provided by developing a capability (BDAC) is relatively small or even not statistically significant. An exception is the social/ environmental performance for which we do not have any evidence of studies to test the relationship between BDAC and SEP.

(5) The types of performance on which the impact of BDA relatively small and by developing a BDAC the impact would improve by more than 100% are the following: competitive advantage (CA), customer satisfaction (CS), organizational agility (OA), decision making effectiveness (DME) and employee development/satisfaction (ED). In other words, for these types of performance developing a capability is critical.

(6) In terms of innovation (IN) and supply chain performance (SCP), the situation is somewhere in between, both BDA and BDAC add a positive and statistically significant effect.

(7) The size of the firm does not seem to play a significant role in this relationship. With very few exceptions it appears that the relationship is not influenced by the sector as well. As we included studies across ten years interval, it appears that there is an increasing trend in terms of the size of the effect. However, the relationship lacks the statistical power to confirm with high certainty that, in time, the positive impact of big data analytics upon performance will be stronger. Nevertheless, there are a lot of factors that incline us to believe that this effect will improve in the future. Some of these are related to the evolution of technological solutions: higher capacities for data capture and storage, large-scale deployment of the internet of things, faster processing speeds, development of software solutions, etc. Also, currently, there is a gap between the supply and demand in terms of specialists. It will be a joint effort for both, the education system and the learning and development departments of organizations to prepare and continuously improve the knowledge and the skills of both managers and data scientists.

Limitations and future research possibilities

When doing a meta-analysis there are always two inherent risks: the *between-study heterogeneity* and *publication bias*. The between-study heterogeneity appears when the true effect size varies across studies.

A high heterogeneity means that the study results vary from very negative to very positive or we have outliers. As we expected, our sample has been impacted by heterogeneity. The first natural solution was to use the random effects model instead of the fixed effect model. After we run the meta-analysis, we checked the indicators which measure the heterogeneity and indeed, it appeared that we faced a very high heterogeneity between the studies we included. It was reassuring however because after we applied some influence analyses and we removed the outliers the overall results did not change significantly. We can say that although we have a great diversity of results among our sample, this does not change in a major way our results. The impact is that the confidence intervals are broader as it adds a degree of uncertainty. We have to say though, that in our case this was a calculated risk. It was one of our initial objectives: to include as many studies as possible, to benefit from a higher statistical power, and to be able to run subgroup analyses.

Publication bias is an interesting risk, as we are more concerned with the missing data. In some sense, this is more uncertain, as we do not know what we do not know. We want our list of studies to be as much comprehensive and representative as possible for our topic. We are ready to accept that we missed some studies if these are random. It becomes a problem when our sample is systematically biased. And this is a risk, as certain pieces of evidence support that the studies which fail to statistically prove their hypothesis have a lower chance of success in terms of being accepted for publishing.

When running the *small study effect method*, we discovered that indeed our sample does not follow a funnel plot form, however, the distribution appeared to be balanced around the pooled effect size. To check further, we applied the *trim and fill method,* through which we removed the outliers and we artificially added some effect sizes. The result was very close to the original one, which confirmed that our result manages to capture the true effect size.

These are some encouraging results. However, between-study heterogeneity and publication bias always offer a dose of uncertainty to the results of a meta-analysis. Also, to cope with publication bias, we used an inclusive searching criterion and the richest search engine (Google Scholar). Additionally, we did not limit our sample to just peer-reviewed articles, but we included also PhD or Master's thesis.

Another limitation of our study is the small sample for some subgroup analyses. Due to this, we lacked the statistical power to prove some relationships at the subgroup level (e.g., sector and country). The fact that we failed to prove that some sectors have additional positive effects, or that the effects are higher within some countries does not allow us to generalize the results. It is not like we can say that the effect is the same no matter the sector. Is more like we cannot confirm that the effect is different within some sectors.

As for *future research possibilities,* we can start from the fact that this is a relatively new movement, a little bit over ten years. We need to be consistent in researching this topic and to follow closely the trend within the next years. The technical solutions as well as the pool of talent are in a tremendous expansion. As big data itself had to reach a certain size in order to offer additional performance is the same with the domain. The more people use big data, the more databases will be interconnected. Larger capacities for computers to process data and higher transfer speeds will enhance as well the impact. All these would be very interesting to be analyzed in the years to come.

We saw that there is a continuously increasing trend for the popularity of this topic. So, for a meta-analysis, this will add more data to the sample and thus increase the statistical power. If more studies are added to the sample, the model can be developed further. For example, for the big data analytics part, we had to limit ourselves to two levels BDA and BDAC. Although we found multiple types of big data analytics: big data analytics capability, data-driven environment, big data investments (announcements), big data resources (knowledge assets), ad-hoc use of big data analytics, routine use of big data analytics, customer analytics, internet of things. But to keep the statistical power to a significant degree we had to merge these into just two tiers depending on the level of integration: big data analytics use (BDA) and big data analytics capability (BDAC).

Based on the big data analytics types we identified (BDA and BDAC) and the types of performance assessed across studies we created a model. Future researchers can use this model for empirical survey-based studies.

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