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Review

Big Data Analytics and Firm Performance: A Systematic Review

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Abstract: The literature on big data analytics and firm performance is still fragmented and lacking in attempts to integrate the current studies' results. This study aims to provide a systematic review of contributions related to big data analytics and firm performance. The authors assess papers listed in the Web of Science index. This study identifies the factors that may influence the adoption of big data analytics in various parts of an organization and categorizes the diverse types of performance that big data analytics can address. Directions for future research are developed from the results. This systematic review proposes to create avenues for both conceptual and empirical research streams by emphasizing the importance of big data analytics in improving firm performance. In addition, this review offers both scholars and practitioners an increased understanding of the link between big data analytics and firm performance.

Keywords: big data analytics; business analytics; firm performance; technology adoption; systematic review

1. Introduction

With the rapid development of big data over the past few years, researchers and practitioners need to consider the means by which they can incorporate the adoption of advanced technologies into their competitive schemes. Big data in company decision-making has recently garnered considerable attention [1], and the number of firms investing in big data analytics to improve their competitive advantage and performance is growing [2]. In order to take full advantage of the fast-expanding data volume, velocity, and variety, techniques and technologies for storing, analyzing, and visualizing data are required, but there has been noticeably less research attention on how firms can embrace these technologies for further improvement [1].

Big data as a high volume, high velocity, and high variety of raw information needs a cost-effective and innovative information analysis technique to capture insights for decision making [3]. Consequently, the topic of big data analytics arises when the concern is analyzing raw data that have not been processed for use and from which hidden information has not yet been extracted. Currently, big data analytics has been considered the predominant method for analyzing big data because of its superior ability to capture huge amounts of raw information and apply the best analytical practices to measure it. It has become a tool by which companies gather varied data and use automatic data analytics to inform appropriate decisions that had previously depended on the judgment and perceptions of decision makers [3,4]. Thus, big data analytics revolves around three key features: the data itself,

the analytics applied to the data, and the presentation of results in a way that allows the creation of business value for firms and their customers.

With the progress of digitalization, more companies are considering using big data and business analytics to analyze available data in order to (1) improve their products and services and (2) support smart decision-making [5,6]. That is to say, organizations need to exploit the full potential of big data and business analytics to gain a competitive advantage in the market. Nevertheless, because big data analytics is still a rapidly developing technological and business practice, there is little research on how to effectively use and exploit it. Even though prior studies have shown the advantages of adopting big data analytics in various contexts, there remains a lack of evidence on how to apply this solution to create a competitive advantage. In the area of business and management, there are a few systematic papers focused on big data analytics, for example, Refs. [1,7–10]. Rialti, Marzi, Ciappei and Busso [7] stated that "minimal attention has been paid to systematizing the literature on big data and dynamic capabilities." In this light, the current study attempts to identify the factors that may influence the use of big data analytics and the capabilities needed for improving firm performance. We, therefore, focus on summarizing and reviewing the available literature to pinpoint themes related to big data analytics and firm performance.

Despite all the benefits that big data may bring to an organization, many companies have decided not to invest in big data analytics. This occurs especially among companies that have not successfully adopted business intelligence [6]. Big data comprises a large volume of data that are produced very rapidly from various sources, and sometimes it is difficult for companies to capture and store it; however, a series of novel technologies have been generated to deal with these mountains of data from various sources [11]. Additionally, some business executives may question whether big data analytics is any different from business intelligence and the process of data mining or whether it represents a new capability whose use demands major funding.

Answering these questions is of vital importance to policy makers investing in the seeding of innovative data analytics projects as well as to business practitioners and scholars. To begin, the authors consider the dissimilarities between big data analytics and traditional business intelligence techniques. Although the era of big data started only in 2005, the volume of big data is growing fast, increasing around 50% annually [12]. Interestingly, a substantial amount of this growth is represented by unstructured data, such as video, images, social media posts, user comments, and any type of data that cannot easily be grouped in recurring fields. Thus, big data is a collection of vast, complex datasets that challenge companies' ability to capture and manage them in a timely manner using the most advanced data management techniques relevant to information processing [13]. In some studies, big data analytics is seen as a fundamental leap from old business-intelligence techniques [3], but it may still be new to researchers in the field of social science. According to Sundblad [14], however, business intelligence is an integral part of most projects that adopt big data analytics, which can provide useful knowledge to companies [15]. Herein, big data analytics is defined as "a collection of data and technology that accesses, integrates, and reports all available data by filtering, correlating, and reporting insights not attainable with past data technologies" [16].

Overall, big data and its analytical methods represent newly emerged opportunities for companies to analyze available data to obtain more information about the status of their business in the market and thus make good decisions to stay competitive and increase their market share. Big data analytics has been used in diverse areas and sectors, such as e-commerce, e-government, and healthcare [17], but other sectors and businesses would benefit from its adoption.

It has been reported that big data analytics can increase the effectiveness and efficiency of firms by allowing them to set appropriate strategies through the lens of data [5,18]. Big data analytics has become a vital element of the decision-making processes of agile organizations [19], and it is claimed that big data analytics produces impressive results in diverse industries. For instance, the majority of retailing companies are currently extending big data capabilities to enhance the customer–relationship management (Tweney [20]), while in the healthcare industry, big data analytics is likely to moderate

operational costs and improve quality of life [21]. In some sectors, such as manufacturing, it is expected to facilitate and improve business-process monitoring [22]. Furthermore, it has become a catalyst for the improvement of supply-chain management, the enrichment of industrial automation [23], and the acceleration of business innovation [16,24]. In addition, big data analytics can optimize prices; increase profit [25]; and maximize sales, financial productivity, and market share [26] as well as return on investment [27–29]. In their research in the context of healthcare, Srinivasan and Arunasalam [30] claim that gaining capability in big data analytics will help firms maintain their competitiveness through cost reduction; for instance, it will help them to reduce waste and fraud. Furthermore, it supports companies to improve their quality of care by improving safety in treatment. In this vein, firms using big data technologies are more likely to convert data into intelligence and insights, improving their productivity and business growth [31].

Big data analytics has been considered a primary capability that can improve a firm's performance [5,9]. An organization that increases its big data analytics capability should be able to maximize its performance. This can be done by developing big data analytics capability and identifying the factors that may positively influence that capability building. Thus, superior firm performance in a big-data–driven environment derives from a perfect combination of all resources, including organizational resources (big data analytics management), physical resources (Information Technology (IT) infrastructure), and human resources (analytics skill or knowledge), which should be unique and inimitable [27,32].

Notably, the available studies of big data analytics are still few and fragmented, especially in the social sciences. Furthermore, the implementation of big data analytics among practitioners is also in its initial phase; therefore, through the lens of a systematic literature review, this study attempts to gain a broad overview of big data analytics and its relationship to firm performance. This study provides direction to researchers and businesses by categorizing the diverse existing models of big data analytics. To assess the use of big data analytics by firms, it is essential to identify its main drivers. Doing so will provide grounds for the claim that the proper implementation of big data analytics allows organizations to effectively exploit big data.

This paper aims to make the following contributions: First, identifying the number of papers available on the Web of Science (WoS) that focus on the use of big data analytics; second, determining the factors that the published papers have identified in the successful use of big data analytics to improve a firm's performance. As such, this paper provides a broad review of big data analytics and firm-performance studies. The next section describes the research methodology of the systematic review, followed by a presentation of the results of the literature analysis, showing the frequency-related findings of the selected papers. A discussion, directions for future research, and a succinct conclusion are provided in the final section.

2. Research Methodology

The research methodology of the literature review is presented in distinct stages. In 2.1, the authors describe the review protocol. The next sub-section explains the inclusion and exclusion criteria for relevant papers, describes the in-depth search for publications, and addresses evaluating the quality of publications, categorizing the data, and synthesizing the findings of previous studies. Each stage is elaborated in the following sub-sections.

2.1. Protocol Development

The initial phase of our systematic literature review involved developing a protocol for further phases. The current study followed the guideline of the Cochrane Handbook for Systematic Reviews of Intervention [33]. The protocol of this review addresses the main objective of this study, which is identifying and synthesizing past findings related to big data analytics and its relation to firm performance. The criteria for inclusion or exclusion of papers, the search strategy, the quality assessment, and the categorization the findings were developed on the basis of that objective. This literature review

aims to understand the factors that may influence the adoption of big data analytics and its impact on firm performance in various industries. To achieve that aim, diverse criteria were identified to categorize the papers, as elaborated in the analysis (Section 3).

2.2. Inclusion, Exclusion, and Search Strategy

The current systematic review aimed to include the most highly ranked papers and considered all relevant publications from 1970 onward, but it was essential to clearly delimit the scope of the review and explicitly demonstrate the procedures. For this purpose, we applied an iterative procedure to identify the relevant articles. We used the Core Collection database of the Web of Science (WoS), one of the more comprehensive electronic databases. Within it, we selected only the Science Citation Index, Social Science Citation Index, and Arts & Humanities Citation Index to limit our search to journal articles. The Conference Proceedings Citation Index, Book Citation Index, and Emerging Sources Citation Index were excluded, and articles and reviews were selected from the document types.

We searched one keyword combination on three dates to extract the relevant articles: "big data analytics" AND "firm performance". The first search returned 24 results, including articles and review papers. We checked the ranking of all the papers, and only those papers indexed by Scopus and ISI were selected. This excluded two papers, leaving 22 papers for review. The same search was performed after a few months (January 2019), and 30 papers were returned by the WoS. The papers and their ranks were checked. At this stage, studies that were clearly not about big data analytics were identified, and only papers that focused on big data and analytical tools were included. This left us with 26 articles. In the final round, June 2019, seven additional articles were identified to be relevant for our analysis. In the screening stage, each author of the present study independently examined the abstracts. After screening all the papers, we reviewed 33 relevant articles.

Finally, a content analysis was performed. Webster and Watson [34] argued that a high-quality review intensively concentrates on concepts. In this study, therefore, each paper was coded according to various criteria. To ensure the validity and reliability of the coding, the authors evaluated the compatibility of each article by screening its contents to ensure that all 33 papers related completely to big data analytics and firm performance. By means of citation probability, we built a corpus of the contributions that had passed meticulous review processes and were most likely to impact future research. Moreover, our results are not subject to any polysemy due to varying contexts. Our study aims to augment the discipline's core progress in understanding big data analytics. Its results are intended to support scholars in precisely framing their studies by taking advantage of our stringent assurance procedure. The publications selected for review comprise those of (Mikalef, Pappas, Krogstie and Giannakos [1], Ghasemaghaei, Hassanein and Turel [5], Ashrafi and Zare Ravasan [6], Ardito, Scuotto, Del Giudice and Petruzzelli [8], Wamba and Mishra [10], Ji-fan Ren, Wamba, Akter, Dubey and Childe [16], Chen, Preston and Swink [31], Akter, Wamba, Gunasekaran, Dubey and Childe [32], Raguseo and Vitari [35], Mandal [36], Zhan, et al. [37], Côrte-Real, et al. [38], Gravili, et al. [39], Gupta and George [40], Hughes [41], Vera-Baquero, et al. [42], Popovič, et al. [43], Kwon, et al. [44], Wamba, et al. [45], Wang and Hajli [46], Wang and Byrd [47], Wang, et al. [48], Wang, et al. [49], Müller, et al. [50], Lai, et al. [51], Rialti, et al. [52], Mikalef, et al. [53,54], Arnaboldi [55], Vidgen, et al. [56], Cillo, et al. [57], Saggi and Jain [58], Wamba, et al. [59]).

3. Analysis of Studies

3.1. Categorization of Publications Based on the WoS

Figure 1 shows the distribution of the papers based on the WoS category. As mentioned above, we used the WoS engine to classify the selected papers. As Figure 1 shows, 14 of the 33 papers are related to the business and management categories; one paper is related to hospitality and tourism, and the rest cover aspects of scientific research. The results reveal a dearth of social science articles related to big data analytics. Maroufkhani, et al. [60] distinguish theory-driven contributions from

technical studies. Based on this categorization, we observe a remarkable concentration of publications in the technical aspect of research and a lack of big data analytics research in social science, except in the hospitality area. Therefore, future scholars can focus attention on social-science-related topics to determine the impact of big data on other areas other than engineering and computer science.

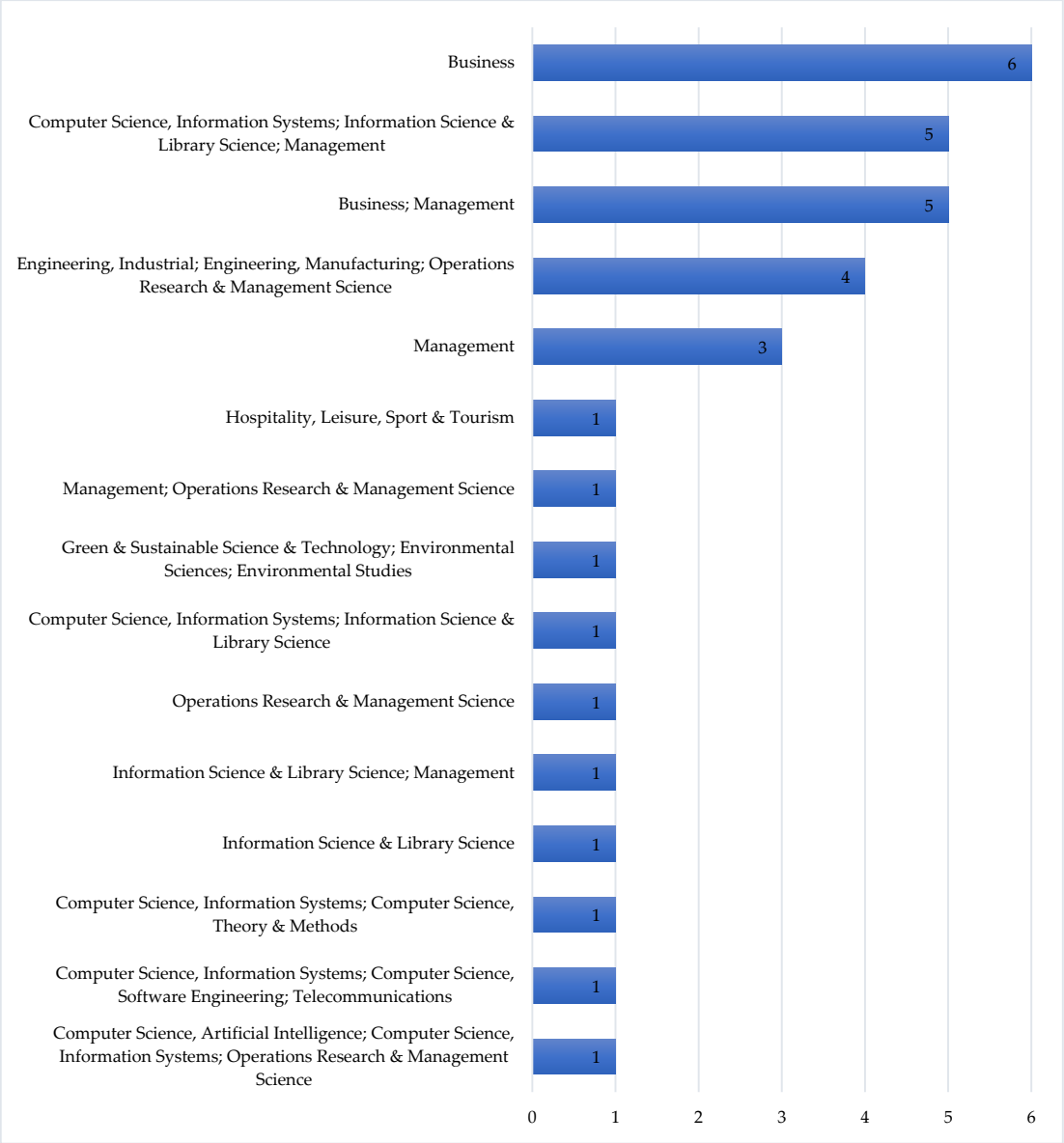

Figure 1. The WoS-related distribution of the papers.

3.2. *Year of Publication, Citations, and Publication Outlet*

Figure 2 illustrates the distribution over time of the selected publications. The topics of big data analytics and firm performance garnered the greatest consideration in 2018, with 2017 next, while only a few studies were published from 2013–2016. Needless to mention that four publications in 2019 is considered a good number since it is just for the first few months of the year. The figure demonstrates that big data analytics and its impact on firm performance is an emerging issue, as an upward trend related to the topic has been established by scholars in recent years. However, more publications are still needed in social science.

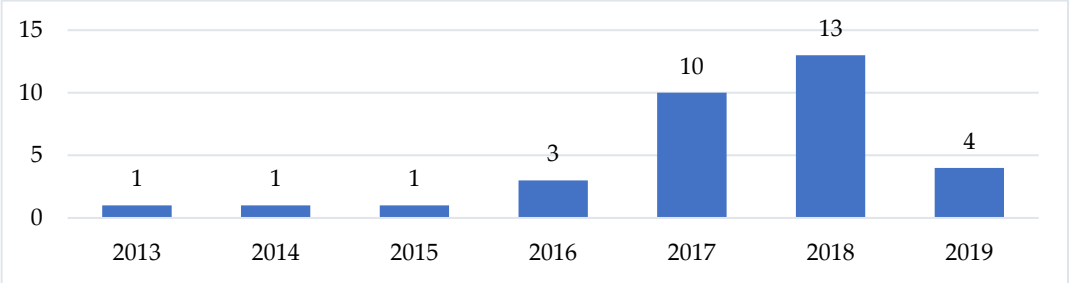

Figure 2. Distribution of the publications by year.

Figure 3 depicts the cumulative number of publications and the cumulative number of citations in each year as well as the ratio of cumulative publications to cumulative citations. As is clear from the relative dimensions of the two bars in the figure, the number of citations is increasing in relation to the number of publications each year. Unsurprisingly, in the early years with only a few papers, citations to those publications were very few. For example, in 2013–2014, only three citations were recorded—all for Vera-Baquero, Colomo-Palacios and Molloy [42]. As the number of papers increases, the field receives more attention, and more citations are recorded as a result of its greater popularity. It is notable that the citations reported in 2018 alone are more than the cumulative citations from 2013–2017 For brevity purpose, we did not include the individual citations for each paper at each year. However, the difference between the two consecutive bars delineates the value of the latter bar. The ratio, depicted as a line in Figure 3, provides an interesting finding. The number of citations received for each paper has an increasing trend over the years. For example, in 2013–2015, with three publications and 27 citations, each paper had nine citations on average. This ratio increased to 19.85 citations per paper among the total of 33 publications recorded in the WoS in 2013–2019. This trend highlights the increasing popularity of big data analytics and firm performance in the literature.

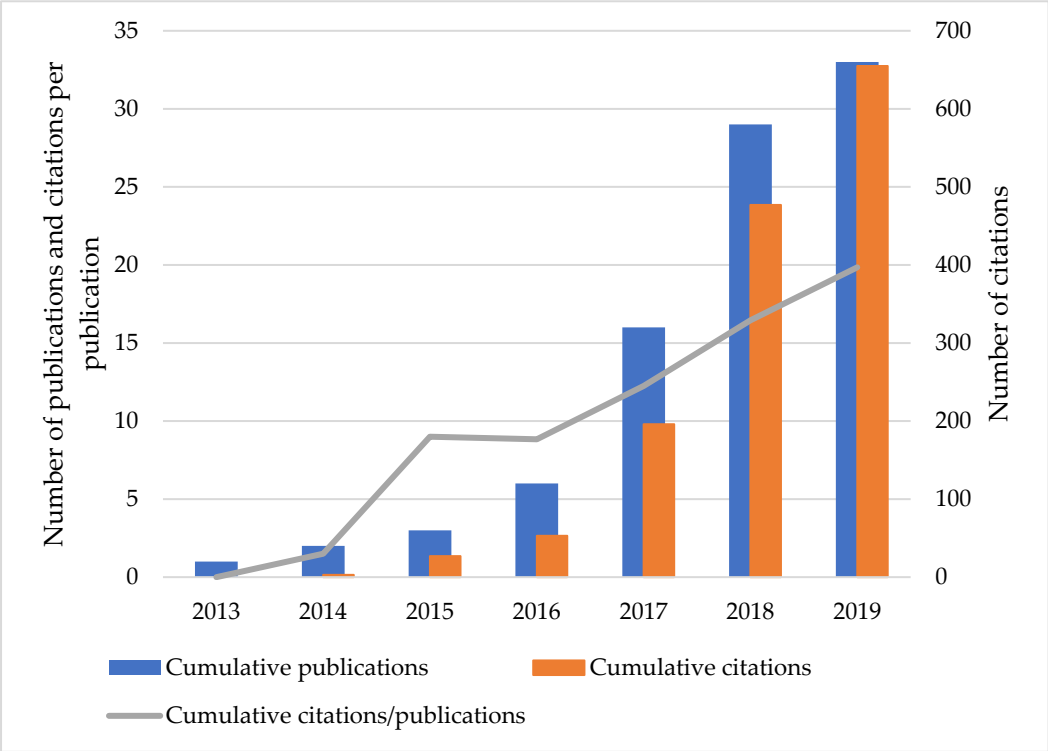

Figure 3. Publications and related citations.

In Table 1, we categorize the papers by the publishing journals. Of the 33 papers, 10 were published in 2017, of which three appeared in the Journal of Business Research. From 2013 to 2019, three publications in that journal appeared in 2017 and one in 2019, making a total of four in the journal. Notably, Business Process Management Journal, a journal in the business and management field, published three papers in 2017–2019. In 2013, we observe only one publication, in a journal related to the IT field, IT Professional. This shows that publications were initially most frequent in the area of IT, but we can observe increasing enthusiasm for publications relevant to big data analytics in social science journals.

Table 1. The number of publications in each journal by year.

Journal Name	Number of Publications							
	2013	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**Total**
Journal of Business Research					3		1	4
Business Process Management Journal					1	1	1	3
Information & Management				1		1		2
International Journal of Logistics Management						2		2
International Journal of Production Economics				1	1			2
International Journal of Production Research					1	1		2
Journal of Management Information Systems			1			1		2
Annals of Operations Research						1		1
Decision Support Systems					1			1
Information Systems and E-Business Management						1		1
Information Systems Frontiers						1		1
International Journal of Information Management		1						1
IT Professional	1							1
Journal of Business & Industrial Marketing						1		1
Journal of Intelligence Studies in Business					1			1
Journal of Knowledge Management					1			1
Journal of Organizational and End User Computing				1				1
Management Research Review						1		1
Information Processing & Management						1		1
Sustainability						1		1
European Journal of Operational Research					1			1
British Journal of Management							1	1
Current Issues in Tourism							1	1
Total Per Year	1	1	1	3	10	13	4	33

3.3. Theory Focus

To develop a profound understanding of big data analytics and firm performance literature, an applicable descriptive analysis was done in the process of conducting the study. We categorized 33 articles based on their underlying theories and the types of performance. Theory building is the process of systematically developing and organizing ideas to explain phenomena that are empirically testable to explain a particular idea [61]. Therefore, categorizing the theories used by past scholars will allow future researchers to understand where ideas about technology or innovation adoption came from in the areas of business and management research. We can say that theory has the capacity to produce new research.

Figure 4 indicates the frequency within which each theory was cited in the publications. Surprisingly, the majority of the papers used the resource-based view and theories derived from the resource-based view (including practice-based view, knowledge-based view, capability building view, value creation view). As we can clearly observe, that theory was cited 18 times. Two papers do not reflect any theory, but both those papers are conceptual literature reviews that focus mainly on identifying research gaps and directions for future research.

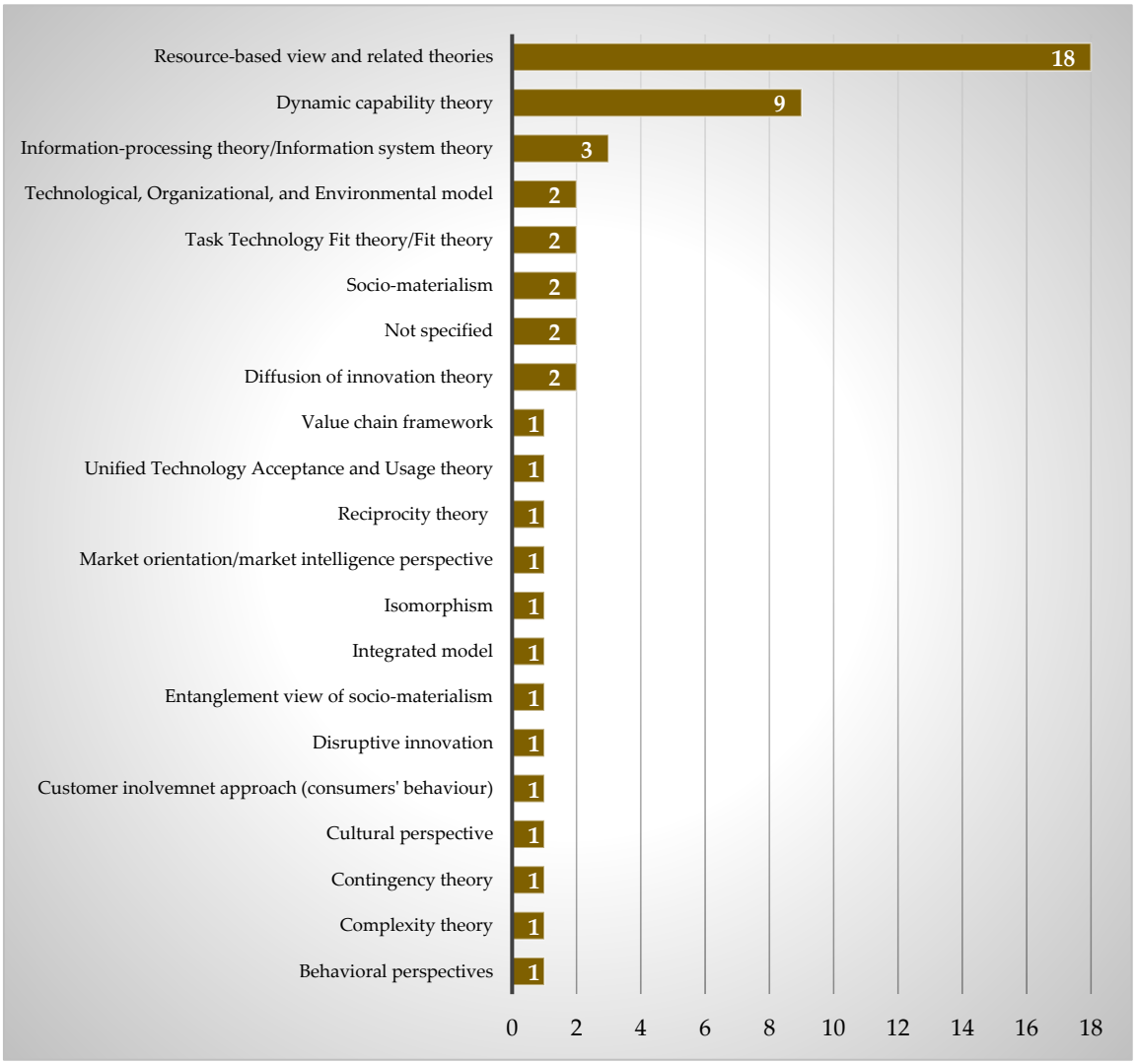

Figure 4. The frequency of theories cited.

In addition to Figure 4, which highlights the popularity of the resource-based view among the authors, Table 2 illustrates another interesting feature related to the theories used, i.e., the number of citations. The 18 papers that reflected the resource-based view received 529 citations in total, or 29.39 citations for each paper, while papers citing the dynamic capability theory received an average of 13.22 citations. The socio-materialism and isomorphism theories attracted much attention to the few authors who incorporated those terminologies in their papers. It is important to mention that the majority of the papers reflected the resource-based view together with other theories. For example, Ji-fan Ren, Wamba, Akter, Dubey and Childe [16] and Akter, Wamba, Gunasekaran, Dubey and Childe [32] utilized socio-materialism in their articles while reflecting the resource-based view in developing their theoretical frameworks, with the same approach being used by Kwon, Lee and Shin [44], albeit with isomorphism. This shows the popularity of particular theories among researchers in the theoretical development stage.

Table 2. Relevant citations in relation to the underlying theories.

Theory	Frequency of Publications	Citations	Publications/Citations
Resource-based view and related theories	18	529	29.39
Dynamic capability theory	9	119	13.22
Information-processing theory/Information system theory	3	107	35.67
Diffusion of innovation theory	2	4	2
Not specified	2	9	4.5
Socio-materialism	2	149	74.5
Task Technology Fit theory/Fit theory	2	24	12
Technological, Organizational, and Environmental model	2	45	22.5
Behavioral perspectives	1	0	0
Complexity theory	1	9	9
Contingency theory	1	1	1
Cultural perspective	1	1	1
Customer involvement approach (consumers' behavior)	1	1	1
Disruptive innovation	1	1	1
Entanglement view of socio-materialism	1	24	24
Integrated model	1	0	0
Isomorphism	1	117	117
Market orientation/market intelligence perspective	1	0	0
Reciprocity theory	1	37	37
Unified Technology Acceptance and Usage theory	1	7	7
Value chain framework	1	3	3

3.4. Type of Performance

Figure 5 shows the classification of articles based on the type of performance studied by the 33 highlighted publications. The majority of the published articles, comprising 27 papers, included non-financial performance in their research. Eleven papers considered both non-financial and financial performance, while three papers focused only on financial performance. Thus, the results of our categorization indicate that concern with financial performance has been lacking in the literature and that most of the research in the fields of big data analytics and firm performance has concentrated on non-financial firm performance. That result may prompt future researchers to test metrically the impact of a technology (such as big data adoption) on firm performance.

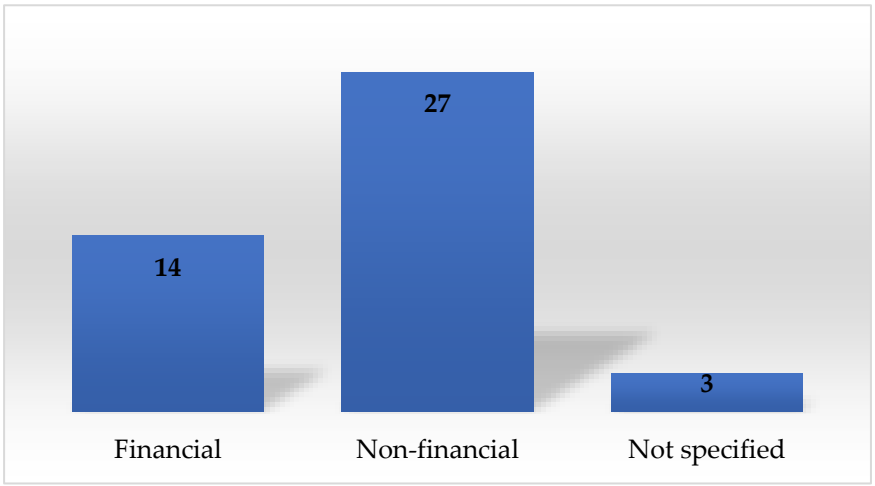

Figure 5. Type of performance investigated.

3.5. Industry Focus and Firm Size

Because the role of industry is important in the performance of firms, in particular Small and Medium Enterprises (SMEs) (Fernández, et al. [62]), the current systematic review applied the Global Industry Classification Standard (GICS) of MSCI [63] to open a new window on industry classification.

Figure 6 presents the classifications. The use of the MSCI industry classifications could be extended in future research, especially in studies whose scope embraces SMEs.

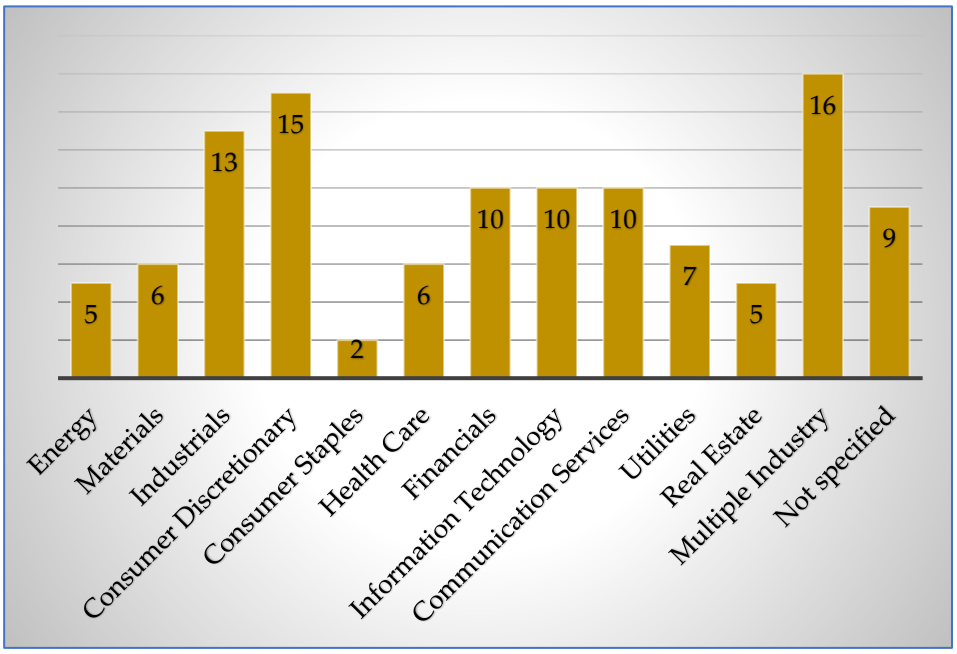

Figure 6. Articles by MSCI industry classification.

The findings of this study show that 16 publications have a multi-industry classification. The industry group that received the greatest attention in the selected publications is consumer discretionary. Figure 6 shows that the consumer staples industry (including food and beverage, household, and personal products) demands more attention from scholars studying big data analytics and firm performance. The result of this review should encourage researchers in the fields of entrepreneurship and strategic management to expand their studies to other industries.

A company must take advantage of technological innovations in a timely manner to become a credible competitor and maintain above-average performance. The characteristics of SMEs, such as their simple organizational structures, complemented by their flexibility and the opportunity-seeking behavior of managers, may inspire them to be more technologically innovative. Therefore, SMEs across industries have a high potential for digitization [64].

With respect to the importance of SMEs, this study evaluated the number of papers focused on them. Figure 7 presents the number of reviewed publications that looked at SMEs' performance along with the industry they focused on. The result shows that one paper has assessed the performance of only SMEs in the area of big data analytics, and it falls in the category of the information technology industry. This indicates that there is a lack of research on the topic of big data in relation to SMEs in industries such as materials, industrials, communication services, and real estate. Although the results show that there are some publications focused on SMEs in other industries, such as consumer discretionary, consumer staples, healthcare, and financial, we were unable to specify the exact number of SMEs, as the researchers investigated a group of industries with diverse firm sizes (SMEs and non-SMEs). Consequently, the recent attention was given mostly to large companies, while studying SMEs could be a potential area of interest for future research. Furthermore, researchers must find industries in which SMEs can adopt big data analytics. Most of the available data are on non-SME organizations, but SMEs contribute significantly to national economic development in the current digitalized world [65], so more studies need to be conducted.

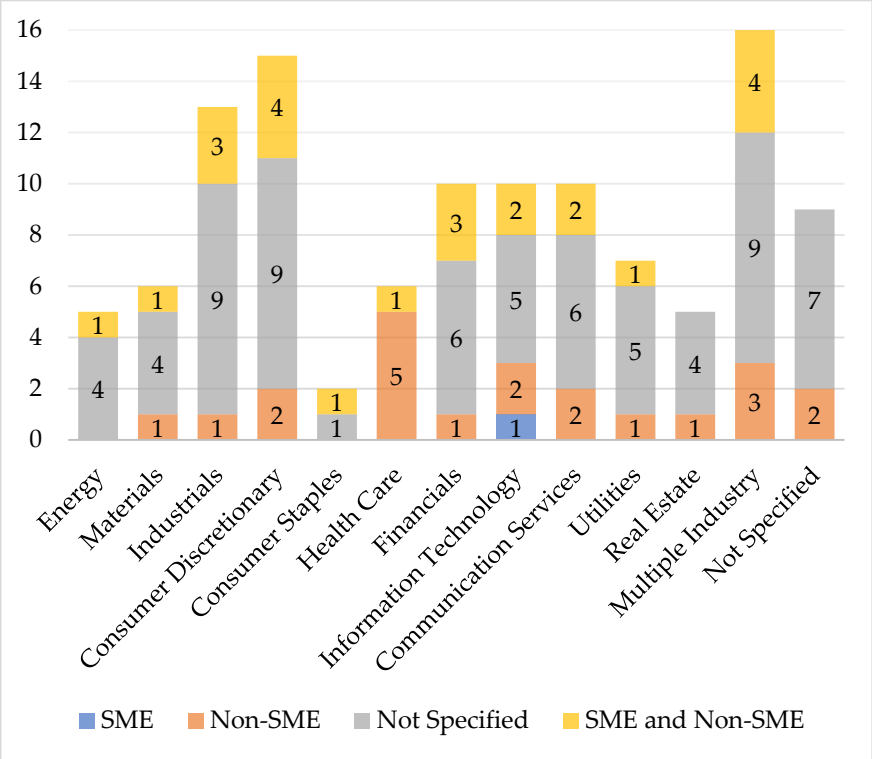

Figure 7. Firm size based on MSCI industry classification.

3.6. Country Focus

In terms of country focus, this study used the World Bank classifications to categorize countries [66]. The results, as depicted in Figure 8, show that one-third of the papers did not use a particular country to frame the research. However, the first largest category is the high-income countries; 15 papers in big data analytics and firm performance conducted their studies in those nations. The results also show that five articles concentrated on middle-income countries. This indicates that working on big data analytics and firm performance in high-income countries has found more favor among scholars, which could be due to a number of reasons. For example, high-income countries may have better access to the knowledge resources needed to take advantage of big data analytics [67]. Thus, our findings on country focus emphasize the need for more studies to discover the barriers that may exist to the adoption of big data in middle-income countries.

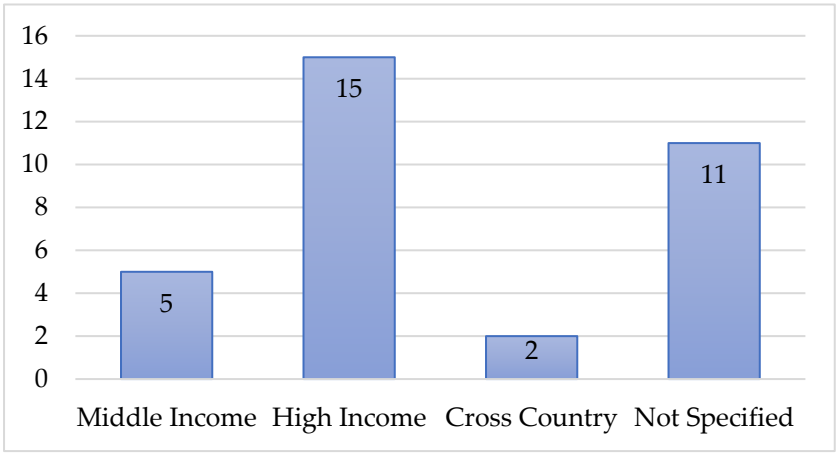

Figure 8. Country-focus distribution of the papers.

3.7. Classification of Articles by Methodology

The distribution of papers by journal and methodology is presented in Table 3. The vast majority of the articles, 15 papers, are survey-based studies, followed by review papers (10 papers) and case studies (nine papers). The results indicate that there is a shortage of exploratory qualitative studies (three papers), mathematical/econometric modelling studies (two papers), action research (one paper), and Delphi (one paper). In addition, it is notable that survey-based articles received the highest number of citations, 452 in total, equivalent to 30.13 per publication, which further accentuates the popularity of this methodological approach. While case studies represented a lower number of publications than review papers, the respective papers received an average of 13.11 citations each, as compared to 8.6 citations for each paper in the review method category. The table also shows which types of methodologies the journals were more interested in. For example, the papers published in the *Journal of Business Research* and *International Journal of Logistics Management* diversify into three groups, case study, survey and exploratory qualitative research and review, case study, and survey, respectively. It is important to highlight that a paper can use two or more methodologies. In our study, the papers that used more than one methodology are as follows: Gravili, Benvenuto, Avram and Viola [39] utilized review and case study; Müller, Fay and vom Brocke [50] utilized survey and mathematical modelling; Popovič, Hackney, Tassabehji and Castelli [43] utilized case study and exploratory; Vidgen, Shaw and Grant [56] utilized case study; Delphi, Mikalef, Boura, Lekakos and Krogstie [54] utilized case study, survey and exploratory; Cillo, Rialti, Del Giudice and Usai [57] utilized case study and exploratory; and Ardito, Scuotto, Del Giudice and Petruzzelli [8] utilized review and case study. While the two papers published in 2018 in *International Journal of Logistic Management* have not so far received a remarkable citation count, four papers published within 2017–2019 in *Journal of Business Research* received a considerable number of citations. This result highlights the higher outreach of *Journal of Business Research* comparatively. In contrast, some of the journals, including *Information Processing & Management*, *Information Systems and E-Business Management*, *IT Professional*, the *Journal of Intelligence Studies in Business*, and the *Journal of Organizational and End User Computing*, have published only review papers. The high number of review papers could reflect the fact that the field is still new and requires adequate exploration of the topic. The remaining journals published articles with both an empirical and review-based focus. In terms of citations, the *Journal of Business Research* has received the highest number of citations. This is followed by the only publication in the *International Journal of Information Management*, a survey paper that has garnered 117 citations so far.

Table 3. Methods used in big data analytics and firm performance research.

Journal	Number of Papers							Total Number of Citations
	Review	Case Study	Survey	Exploratory Qualitative Research	Mathematical or Econometric Modelling	Action Research	Delphi	
Journal of Business Research	0	2	3	1	0	0	0	146
Business Process Management Journal	3	1	0	0	0	0	0	9
International Journal of Logistics Management	1	1	1	0	0	0	0	4
Journal of Management Information Systems	0	0	2	0	1	0	0	45
Current Issues in Tourism	0	1	0	1	0	0	0	0
European Journal of Operational Research	0	1	0	0	0	0	1	17
Information & Management	1	0	1	0	0	0	0	56
Information Systems Frontiers	0	1	0	1	0	0	0	5
International Journal of Production Economics	0	1	0	0	1	0	0	62
International Journal of Production Research	0	0	2	0	0	0	0	103
Annals of Operations Research	0	1	0	0	0	0	0	1
British Journal of Management	0	0	1	0	0	0	0	1
Decision Support Systems	0	0	1	0	0	0	0	9
Information Processing & Management	1	0	0	0	0	0	0	7
Information Systems and E-Business Management	1	0	0	0	0	0	0	15
International Journal of Information Management	0	0	1	0	0	0	0	117
IT Professional	1	0	0	0	0	0	0	37
Journal of Business & Industrial Marketing	0	0	1	0	0	0	0	0
Journal of Intelligence Studies in Business	1	0	0	0	0	0	0	1
Journal of Knowledge Management	0	0	1	0	0	0	0	15
Journal of Organizational and End User Computing	1	0	0	0	0	0	0	4
Management Research Review	0	0	1	0	0	0	0	0
Sustainability	0	0	0	0	0	1	0	1
Total number of papers	10	9	15	3	2	1	1	-
Total number of citations	86	118	452	6	6	1	17	655
Citations/publications	8.6	13.11	30.13	2	3	1	17	-

3.8. Structuring the Contribution based on the Terms and Factors that Lead to Successful Use of Big Data Analytics and Improvement of Firm Performance

This systematic review provides a direction for future researchers to find the terms that have a connection with big data and big data analytics. It can help scholars distinguish the exact difference between big data analytics, data analytics, and business intelligence, as the topic of big data is in its initial phases among researchers and practitioners. It will be helpful to have a concise elaboration of these terms to prevent their being used interchangeably. In addition, it may be observed that other terms, such as *big data analytics solution*, *business analytics*, *social media analytics*, and *big data analytics-capable business process management systems* have been used in the context of big data analytics studies (Table 4). While the *big data analytics* alone is the most frequent term used, the keyword *capability*, either *big data analytics capability* or *business analytics capability*, received noteworthy attention by scholars. Nonetheless, future studies might focus on other terms, such as *big data analytics solution*, to further measure the terms used for big data analytics. Big data analytics is a topic associated mainly with computer science and IT, but social scientists have shown interest in the topic. Therefore, there is a need to learn how to measure big data analytics in social sciences, beyond its technical assessment. For instance, in the studies by (Ji-fan Ren, Wamba, Akter, Dubey and Childe [16], Raguseo and Vitari [35]), the measurement considered for big data analytics is the business value of big data for organizations. As we learned from the results, these three studies used the term *big data analytics solution*, in which the focus is on the business value of big data analytics, while using the same terms, *big data* and *big data analytics*. Future social science studies need to measure more of these terms and may even use different measurements within the general concept of big data analytics.

Table 4. Frequency of terms used.

Term	Frequency of Use
Big data analytics capability/assets	15
Big data analytics-capable business process management systems	2
Data analytics	5
Big data analytics solution	4
Business intelligence	3
Business analytics/Business analytics capabilities	11
Social media analytics	3
Big data analytics	30

Figure 9 identifies the factors that may positively influence the use of big data analytics to improve firm performance. The results show that the individual aspect, such as the technical knowledge and capability of personnel, is a key factor in allowing practitioners to adopt big data analytics and subsequently improve their firm's performance. The next important factor identified is the organizational aspect, which was highlighted by 18 papers. This may comprise top management support, organizational readiness, perceived benefits, business value perception, decision maker's attitude, culture, reputation and infrastructure. This is followed by big data analytics capability (13 articles). In general, big data analytics capability is the ability of a company to deliver valuable insights by means of data management, infrastructure, technology, and talent through firm-wide processes, roles and structures to create a competitive advantage for the business [54]. Some definitions of big data analytics capabilities emphasize the procedures that must be adopted to exploit big data [68], while others focus on investing the required resources and their alignment with the policy [69]. In principle, the term *big data analytics capability* extends the approach of big data to embrace all associated resources that are imperative for taking full advantage of big data. With respect to the definition of big data analytics capabilities, three factors—including individual, organizational, and data related aspects—can be a part of big data analytics capability, and among the papers reviewed, 11 articles emphasized the data-related aspect. The *Data-related aspect*, in this study, embraces any

factor related to the quality of the data, such as the quality of the sources of the data, the ability to access the data and information, the quality of the information obtained from internal or external sources, the way information disseminates, the quality of the system, and the applications that can be used in the analysis of the data, information processing and information learning, and data-driven culture and strategy.

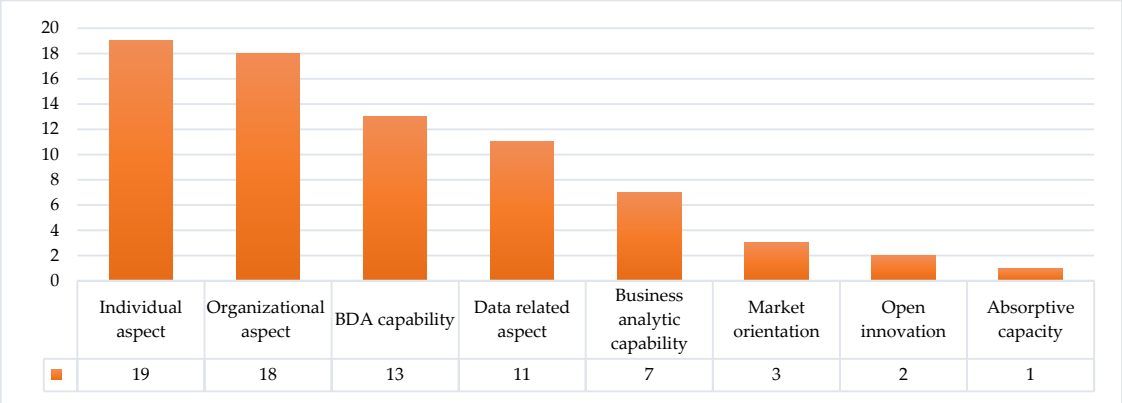

Figure 9. Factors leading to the successful use of big data analytics and improvement of firm performance.

As can be readily observed, most studies focused on the individual aspect, which considers the technical knowledge of people in the organization. Few papers stressed the importance of other factors, such as absorptive capacity, open innovation, and market orientation, as researchers seemed to favor organizational performance in the context of big data analytics. A total of six papers found that having abilities in terms of absorptive capacity, open innovation, and market orientation helped firms fulfill customers' needs and consequently enhanced their performance by taking advantage of big data.

4. Discussion, Future Research Directions, and Conclusions

This study presents an overview of publications on big data analytics and firm performance by means of the descriptive and content analysis of highly-ranked articles. To extract the most relevant articles, the authors used predefined keywords to search for studies in the WoS database. The papers were screened by assessing the articles through titles, abstracts, objectives, and conclusions. In the screening stage, we excluded those that did not fulfill the inclusion criteria. For example, the reviewed papers must first have been in the Science Citation Index, Social Science Citation Index, or Arts & Humanities Citation Index. Second, they had to be completely related to big data analytics and firm performance. Third, they necessarily had to be ISI- and Scopus-indexed journal articles. To give a precise view of big data analytics and firm performance research, we extracted and analyzed a set of 33 articles. Through the lens of the systematic review method, we identified the key contributing factors that may influence the adoption of big data analytics and consequently improve firm performance. These factors include individual aspect, organizational aspect, big data analytics capability, data-related aspect, business analytics capability, absorptive capacity, open innovation, and market orientation. Furthermore, the similar terms used across a broad spectrum of disciplines were identified. This will help future researchers, in particular social science researchers, to appreciate what terms are related to big data analytics and firm performance, allowing them to categorize the similar and different definitions developed by other studies. Thus, this paper generates knowledge through its systematic review in the area of big data analytics and provides directions for future researchers. We can see from the descriptive results that *big data analytics capabilities/assets* is the term most frequently used by scholars other than *big data analytics*. The latter term is used in almost all the articles reviewed. Two of the three papers that did not use the term *big data analytics* are those of Ghasemaghaei, Hassanein and Turel [5] and Arnaboldi [55], who use the keyword *data analytics*. Another is that of Ashrafi and

Zare Ravasan [6], who use the keyword *business analytics*. However, the authors of the present review included those papers because the contents of the studies fulfilled the objective of the current study. Furthermore, business intelligence and data analytics are related to big data, both of them contributing to the decision-making process in organizations by taking advantage of big data [14,15]. In this light, Santoro et al. [70] believed that big data is compatible with the business intelligence techniques that are needed to provide intelligent assistance for organizational processes.

According to the statistics documented in our study, an interest for future researchers is the study of the factors influencing the adoption of big data analytics and the creation of business value for organizations. Empirical research that looks at the value of big data analytics remains insufficient, and, therefore, leaves industries insecure once confronted in employing such investments in their businesses [54]. To substantiate theoretical and practical implications of research for future scholars, researchers must understand the core elements that may influence the implementation of big data analytics and how such investments lead to business value [71]. The adoption of big data analytics has become common in large companies, such as those in healthcare [72,73]. Recent researchers, such as Amato et al. [74], also look for new applications of big data in that industry to improve the performance of the healthcare industry. The use of big data analytics can be external or internal. For example, if some firms, such as SMEs, have little ability to directly use the tools and techniques required for analyzing big data, they can seek help by outsourcing the analysis of their acquired data and thus build business value for their firms. Previous researchers, for instance, Ghobakhloo, et al. [75], have discovered the factors that may influence the adoption of information technology among SMEs.

Thus, future scholars can focus more on the factors that may help SMEs to adopt big data analytics, thus ensuring that they can benefit from the adoption of big data analytics. As SMEs contribute substantially to the economic growth of nations, more studies in the area of big data should be conducted on this type of firm and the industries in which they operate. Recently, research was performed by Mikalef, Boura, Lekakos and Krogstie [54] which focused on the big data analytics and firm performance including SMEs. Mikalef, Boura, Lekakos and Krogstie [54] found out that technological resources in terms of technological and technical assets contribute more towards a firm performance improvement in an environment with moderate uncertainty, whereas organizational resources such as managerial aspects and individual skills play essential roles in a highly uncertain environment. In addition, in line with the result obtained from the current systematic review, Mikalef, Boura, Lekakos and Krogstie [53] discovered that technical skills are key elements in enabling firms to leverage the potential of big data analytics. Technical skills, as an individual aspect, are the factors that have received much more attention in recent years from data scientists, although attention on the importance of organizational aspects to benefit big data analytics has also increased.

In line with the result obtained from the current study, future scholars of business and management are encouraged to deliver more empirical studies on the related topic and particularly the impact of different factors such as the impact of the data-related aspect, absorptive capacity, open innovation, and market orientation. In addition, the results reveals that middle-income countries are currently less studied. Generally, studies on big data and big data analytics have concentrated on large companies in high-income nations; therefore, it will be interesting to find more empirical research on SMEs in middle-income nations. Additionally, this study tried to determine the terms that are used synonymously with *big data analytics*. Future research could investigate those terms to find more similarities and differences between the terms to avoid confusion among novice social science researchers new to the field of big data.

This study provides a reference for scholars and practitioners identifying the challenges related to big data analytics. Future researchers can identify the journals that fit their research approach to facilitate the diverse publication of conceptual and empirical papers with different methodologies. As the field is still new to social scientists, future scholars may attempt to publish articles about big data analytics in various areas of social science and management. In addition, with the evolution of big data in a digitalized world, businesses and entrepreneurs may be inspired to learn how to adopt and

implement big data analytics and business analytics rather than merely using devices that produce big data. Firms, especially startups and new firms supported by incubators, must continually improve their performance, so studying the elements that contribute to the adoption of big data analytics will help them to use it in a manner befitting their contexts. Ferraris, et al. [76] stated that big data analytics has the potential to change the way companies practice and enhance their performance through better understanding, managing, processing, and using of vast amounts of raw data obtaining from various sources (internal and external). Those companies that developed their big data analytics capabilities more in terms of technological and organizational aspects have been able to improve their performance subsequently. More precisely, firms must first initiate a coherent and unambiguous data-driven strategy if they aim to benefit from big data analytics. Second, firms have to employ the right human resources, with the right skills and expertise in big data. Finally, despite the importance of the technological aspect in big data analytics adoption, the organizational aspect should not deny a data-driven culture [54,56]. For instance, firms need to provide a robust infrastructure to maintain their resilience and take advantage of the data-driven culture. It will also increase their ability to collect and analyze data from different sources [77].

Notwithstanding, there are other factors in the successful adoption of big data analytics that are not discussed in this paper. For example, Ferraris, et al. [76] have found that knowledge management orientation can play a significant role in increasing the impact of big data analytics capabilities and firm performance [76]. In another study, Dremel, et al. [78] found that actualizing big data analytics affordances in companies can be affected by various social and technical elements, for example, human resources expertise, organizational processes, and social capabilities. Thus, studying the socio-technical aspect can be a direction for future research on big data analytics at the organizational level. In addition, Ghasemaghaei [79] showed that other than the organizational and technical aspect, social factors such as psychological readiness are core elements which can influence an organizations' decision to be able to create value from big data analytics adoption. On the other hand, Conboy, et al. [80] identified the temporal factors that may affect the business value of analytics in a setting. Conboy, Dennehy and O'Connor [80] defined these factors to include the followings: "appropriate use of clock and event time in analytics, appropriate use of subjective and objective time in analytics, appropriate use of analytics to predict challenges around social constructions of time, appropriate management of multiple speeds of analytics, appropriate communication of real-time data in analytics, appropriate management of different perceptions of time in analytics, appropriate management of different temporal personalities in analytics".

Based on the result obtained from current systematic research work, this study recommends that future scholars conduct more systematic and empirical studies on the use of big data analytics in diverse types and sizes of companies to explore what other factors may help an organization to amplify the adoption of big data analytics for improvement of their performance. Future scholars may expand the domain of search of big data analytics and business analytics in the area of business and management to capture more studies including those missing in WoS Core Collection as other research works have not appeared in our search result but deserve to be reviewed systematically (for example, Refs [7,8,70,76,78–80]).

Although most articles in this study are mainly business- and management-oriented, there are other reputable ones [55,57] which tie social science and managerial issues in the context of big data analytics. As such, this systematic review provides a multidisciplinary stream of research and opens an avenue for future researchers to explore social-science-related factors tied with big data analytics usage. Furthermore, it will be possible to make more comprehensive studies from an integrated perspective of social science, behavioral, and managerial issues. The increasing popularity of big data analytics in different areas such as business, science, engineering, and social science signifies its multidisciplinary nature to be appreciated by different groups of societies, businesses and policy makers around the world.

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