The big data-business strategy interconnection: a grand challenge for knowledge management. A review and future perspectives

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Abstract
Purpose – Designing knowledge management (KM) systems capable of transforming big data into information characterised by strategic value is a major challenge faced nowadays by firms in almost all industries. However, in the managerial field, big data is now mainly used to support operational activities while its strategic potential is still largely unexploited. Based on these considerations, this study proposes an overview of the literature regarding the relationship between big data and business strategy.

Design/methodology/approach – A bibliographic coupling method is applied over a dataset of 128 peer-reviewed articles, published from 2013 (first year when articles regarding the big data-business strategy relationship were published) to 2019. Thereafter, a systematic literature review is presented on 116 papers, which were found to be interconnected based on the VOSviewer algorithm.

Findings – This study discovers the existence of four thematic clusters. Three of the clusters relate to the following topics: big data and supply chain strategy; big data, personalisation and co-creation strategies and big data, strategic planning and strategic value creation. The fourth cluster concerns the relationship between big data and KM and represents a ‘bridge’ between the other three clusters.

Research limitations/implications – Based on the bibliometric analysis and the systematic literature review, this study identifies relevant understudied topics and research gaps, which are suggested as future research directions.

Originality/value – This is the first study to systematise and discuss the literature concerning the relationship between big data and firm strategy.

Keywords Bibliometric analysis, Strategy, Big data, Research agenda, Systematisation of literature

Paper type Literature review

1. Introduction

Big data (BD) has been regarded as ‘the next frontier for innovation, competition, and productivity’ (Manyika et al., 2011, p. 1) and the main responsible for the next ‘management revolution’ (McAfee and Brynjolfsson, 2012, p. 60). Through the deployment of BD, firms are able to identify opportunities, support decision-making, monitor and improve infra- and inter-company operational processes and investigate changes in consumer tastes and behaviours (Bresciani et al., 2018; Santoro et al., 2019). The success of business strategies based on BD depends on the company’s ability to overcome technological barriers and cultural impediments that hinder their implementation (Tabesh et al., 2019). Because of the growing diffusion of BD in the business context, firms increasingly need to redefine their knowledge management (KM) systems to make them capable of managing the different types of complex data available in a dynamic and transparent manner (Intezari and Gressel, 2017). This need derives from a peculiar feature that distinguishes the knowledge...
extracted from BD; in fact, it is neither explicit nor tacit but ‘emergent’ because it comes up suddenly and unexpectedly during the observation of the external environment (Patel and Ghoneim, 2011). This leads to define the business intelligence systems of data-driven organisations as socio-technical knowledge systems where BD collected, stored and analysed by machines triggers interactions between data scientists and decision-makers; the latter in turn resort to their past experiences to verify, make sense of and codify the insights extracted, thus contributing to refining the rules and programs on which machine learning routines are based (Lugmayr et al., 2017). This circuit formed by observations and actions taking place continuously and in parallel can be described by the expression ‘knowing through making’ (Mäkelä, 2007, p. 159), which emphasises how the mutual influence of data analytics activities and human analysts’ creative efforts favours the emergence of new valuable knowledge from BD, which bears a potential positive effect on the business in terms of product, service, decision and process optimisation (Kaufmann, 2019).

Designing KM infrastructures capable of transforming BD into strategic information is one of the main challenges faced by firms in recent years. However, in the managerial field, BD is nowadays primarily used to support operational activities while their strategic potential is still largely unexploited. Moreover, no study has so far proposed a systematisation of the literature concerning the relationship between BD and firm strategy. Based on these considerations, this study aims to bridge that gap. We hereby consider ‘firm strategy’ as a broad concept including organisational decisions of strategic significance related to any company area (from corporate to business and functional levels), strategic purpose (from competitive to growth objectives) and potentiality of overcoming the state-of-the-art (from innovative to disruptive potentialities) for which BD can represent a valuable support (Mazzei and Noble, 2017; Prescott, 2014). Section 2 presents a short review of the fundamental concepts inherent to the management of BD, which is functional to highlight the potential benefits deriving from its use for business strategic decision-making. Section 3 describes the methods used in the study. Section 4 discusses the results of the conducted literature review. Section 5 outlines some possible future research directions inspired by this study. Finally, Section 6 presents our conclusions.

2. Theoretical background

BD can be defined as data with high informative potential whose size and complexity prevent traditional database software from collecting, storing, managing, processing and analysing it (Manyika et al., 2011). To distinguish BD from traditional datasets, seven dimensions have been identified in the literature, known as the 7 Vs (Mishra et al., 2017). Four of the 7 Vs define the concept of BD: data characterised by considerable size (volume) and heterogeneous nature (variety), rapidly generated and processed (velocity) and subject to unpredictable fluctuations over time (variability). The other three Vs represent desirable attributes of BD, in terms of the insights (value) obtainable, as well as the reliability (veracity) and the graphic representativeness (visualisation) of the information attainable. An organisation’s ability to effectively implement BD collection and analysis processes to extract valuable information (i.e., BD analytics capabilities; BDAC) is based on the availability of a set of key resources (Mikalef et al., 2017). In this regard, Gupta and George (2016) distinguish three types of resources that are essential for the development of BDAC: tangible resources, intangible resources and human skills. Tangible resources are represented by internal and external data integration techniques, data storage, processing, analysis and visualisation technologies and investments dedicated to BD initiatives (Gupta and George, 2016). Intangible resources include a corporate culture oriented towards data-driven and evidence-based decision-making at any level of the organisation (Ross et al., 2013) and the intensity of organisational learning, which represents the extent to which the firm acquires, shares, interprets, stocks and applies knowledge extracted from BD (Pérez
Finally, human skills indicate the technical, managerial and relational skills held by specialist personnel (e.g. data analysts and data scientists) and other employees, which are necessary to effectively implement BD analytics (BDA; Fosso Wamba et al. (2017)). BDA are tools that can help organisations ‘in the discovery of hidden knowledge and generation of new knowledge’ originating from multiple sources (Khan and Vorley, 2017, p. 18). Developing adequate BDAC allows firms to effectively exploit the insights extracted from large datasets by making them available for business decision-making through advanced KM systems.

Today, BD is mainly used to support company activities at an operational level, such as procurement, production, warehouse management and distribution, to increase the rationality, efficiency and speed of routine and recurring decisions (Power, 2015). However, a qualitative leap, aimed at aligning BDAC with the needs of strategic activities, would allow companies to better exploit their information resources, increase the existing synergies between business functions, seize new market opportunities and obtain better performances (Akter et al., 2016). The firms that are fully aware of the fundamental support that can be provided by BDA to strategic decisions are better prepared to successfully face the challenges of today’s digital revolution (LaValle et al., 2011; Power, 2015). Specifically, the ability to use descriptive, predictive and prescriptive BDA-enabled techniques, which combine quantitative data with soft elements such as knowledge and managerial intuition, allows to transform the insights emerging from BD into highly valuable and inimitable resources, which can effectively support the processes of strategic orientation, environment observation, formulation and implementation of the chosen strategy (Kunc and O’Brien, 2019).

Based on these premises, the present paper performs a bibliometric analysis, coupled with a systematic literature review, with the aim of offering an overview of the evolution of the literature regarding the BD-business strategy relationship published over the last seven years. Based on the results of the systematic literature review, this study identifies relevant understudied topics and research gaps, which are suggested as future research directions.

3. Methodology

To provide a reliable and sufficiently in-depth review of the emerging literature on the relationship between BD and business strategy, this study uses a mixed method. After conducting a bibliometric analysis based on the visualisation of similarities (VOS; Van Eck and Waltman, 2010), we present a systematic literature review (Tranfield et al., 2003). This methodology has proved useful in many disciplinary contexts because it identifies the underlying research strands of a given field of study by synthesising and representing high volumes of bibliographic data. The analysis was developed through five stages. The first phase, which took place in January 2020, comprised selecting the research query. To obtain a search criterion able to return an exhaustive list of contributions in the literature that investigate the relationship between BD and strategy, several iterations were carried out. The following query: ‘“TITLE-ABS-KEY(“big data” AND ”strategy””)” was performed. The ““TITLE-ABS-KEY”” operator limits the research for the chosen terms to the title, the abstract and the keywords of the relevant papers.

This query was performed on the Scopus database, which represents the most comprehensive data source to retrieve high-quality and peer-reviewed publications for emerging fields of study (Falagas et al., 2008). The search was limited to

- articles, articles in press and reviews that have undergone a double-blind peer-review process (Grégoire et al., 2011);
- documents published on or before December 31, 2019; and
specific disciplinary areas that might involve BD application in business sciences, i.e. Business, Management and Accounting, Social Sciences, Decision Sciences and Economics, Econometrics and Finance.

The retrieved data was cross-checked by applying the same research string on the Web of Science and EBSCO Business Premier databases. This analysis did not identify any missing data, thus confirming the validity of using both our query string and the Scopus database.

In the second phase, three out of the four authors performed an independent screening of the 988 papers included in the initial dataset. This screening led to the removal of a large number of papers that did not relate to the theme object of this study, as summarised in Figure 1. Some of the excluded papers did not focus on BD nor business strategy, while others did not analyse any connection between the two themes. In line with the best methodological practices (Tranfield et al., 2003), three out of the four authors independently analysed the 988 papers. For the screening phase, Krippendorf’s alpha coefficient (K) served as a statistical measure of the agreement achieved. The resulted K was higher than 0.80. Such value indicates robust convergence and strong inter-reliability of the performed selection process. After adopting such selective criteria, the final dataset was reduced to 128 papers.

In the third research phase, the study performed a bibliometric analysis on the final dataset. Specifically, a series of bibliometric activity indicators, concerning the distribution of papers per year, author, journal and country, were first calculated (Todeschini and Baccini, 2016; see Section 4.1). Subsequently, we moved to the core of the bibliometric investigation using VOSviewer 1.6.10. The software was used for the similarity analysis and aggregating papers through bibliographic coupling (Van Eck and Waltman, 2010). Bibliographic coupling occurs when two contributions both refer to a third contribution within their bibliographies. This method is useful for mapping the research strands relating to a specific developing literature and for identifying emerging future trends (Boyack and Klavans, 2010). The algorithm considers the number of shared references between documents to group them into different clusters (Van Eck and Waltman, 2010). Note that 116 out of the total 128 papers resulted interconnected with common references, giving form to a four-cluster structure (Section 4.2). If papers belong to the same cluster, they are strongly linked.
together and may represent a univocal stream of research or approach (Van Eck and Waltman, 2010).

In the fourth phase, always in line with the best methodological practices (Tranfield et al., 2003), three out of the four authors independently scored these 116 papers according to their relevance for the main topics of each cluster. This step was necessary to focus the analysis on the most relevant papers and make the results of our study as pertinent and significant as possible (Tranfield et al., 2003). It was performed by the authors based on their experience and expertise in the field of BD and strategy. Krippendorf’s alpha coefficient (K) was applied as a statistical measure of the agreement achieved. The resulted K was higher than 0.80, showing a robust convergence and a strong inter-reliability of the process. Through this final step, a restricted dataset, composed of 54 papers (around 42% of the total dataset), was selected.

In the fifth and final phase, a systematic literature review was performed (Tranfield et al., 2003).

4. Results

4.1 Results of the bibliometric analysis

In this section, we analyse a series of bibliometric activity indicators (Table 1).

The distribution of papers by year of publication shows how the field of study is subjected to a progressively increasing academic interest with 2018 being the most productive year.

There are no particularly prolific researchers (less than 10% of the selected authors produced more than one article), probably because of the still embryonic state of the thematic area object of our analysis. The data exposed shows a high degree of variety in the disciplinary areas of the journals where the contributions were published in accordance with the semantic breadth of the reading key (strategy) with which the topic of BD is investigated. Finally, the distribution by country shows that Europe is overall the most prolific continent to date (approximately 47% of the contributions).

4.2 Results of the visualisation of similarities clustering process and the systematic literature review

The cluster structure (Figure 2) indicates that papers are well-connected and consider fairly similar streams of literature. The VOS analysis allowed us to identify a four-cluster structure with two clusters (i.e. the red and the blue ones) being the best defined. The green cluster can be considered, by position and content, as a ‘bridge’ connecting the other three clusters. In fact, it collects studies that highlight how BDA can support knowledge management strategy, allowing information to be extracted from BD and converted into valuable knowledge, sharable inside and outside the organisation.

The yellow cluster assembles studies that examine the impact of BD on strategic supply chain (SC) management. The red cluster aggregates contributions that explore the opportunities offered by BD for the personalisation of marketing and innovation strategies. The blue cluster groups studies that focus on BD-driven value creation strategies. Figure 3 shows the main topics covered in each cluster, with indication of the related exemplary references.

In the following paragraphs, the results of the systematic literature review conducted on each cluster are presented.

4.2.1 Yellow cluster: Big data and supply chain strategy. This cluster aggregates studies that highlight how BDA, managed through shared platforms, allow the development of effective SC management strategies and improve the collaboration between SC actors and
Brinch (2018) shows how the use of a properly articulated ecosystem of BD related to infra- and inter-organisational processes can provide new opportunities regarding the optimisation, innovation and reorganisation of SC activities. Specifically, at a strategic level, BDA can be used to support strategic sourcing, SC network configuration and new product design and development activities (Wang et al., 2016).
With reference to strategic sourcing activities, BDA enable the construction of cost prediction and risk assessment models. These models prove useful to analyse the spending profiles of current and potential suppliers, select new suppliers based on the best value proposals and monitor the activity of existing suppliers and supply market dynamics to avoid risks of interruptions within the production cycle (Handfield et al., 2019; Wang et al., 2016). With regard to the physical configuration of the SC, BDA can support decisions regarding the number, position and size of production plants and distribution centres, primarily through optimisation and what-if analysis techniques (Nguyen Dang Tuan et al., 2019). Finally, BDA speed up new product development processes and ensure their adequacy with respect to the quality standards and cost targets (Wang et al., 2016).

To assess the extent to which the company uses BDA to make strategic decisions, Wang et al. (2016) propose a maturity framework that considers three strategic objectives relating to the SC: collaboration, agility and sustainability.

Firstly, BD facilitates the collaboration with business partners, which guarantees knowledge sharing and better decision-making within the SC. Nagy et al. (2018) argue that Industry 4.0 technologies help develop a ‘digital ecosystem’ based on collaborations with suppliers, customers and other strategic partners, where relevant data and information are shared and available at any time within the cloud, thus allowing to develop a really interconnected and ‘customer-centric’ SC. An example of this ecosystem is provided by Navickas and Gružauskas (2016) who focus on small and medium-sized enterprises operating in the food industry market niches. The authors suggest that these companies form collaborative clusters to exploit the SC digitisation so as to optimise logistics costs and shared profits and increase their competitiveness. The development of an effective shared platform between members of the same SC can be achieved through appropriate KM systems, allowing
business partners to have access to the same valuable and reliable information usable for both individual and joint decision-making.

Secondly, the use of BDA increases SC agility, which can be defined as the ability to monitor and respond to external changes in real time. In this regard, Fosso Wamba et al. (2019) demonstrate the positive impact of BDA-enabled dynamic capability on the degree of agility, adaptability and consequently ambidexterity of the SC. Richey et al. (2016) argue that by using BDA, a firm can connect technology, market, consumer needs and innovation, reconfigure and adapt its resources and capabilities and therefore deal with environmental changes with greater readiness. In the face of an increasing complexity characterising the SC, BDA usage allows to moderate this uncertainty by guaranteeing a greater transparency of the collected information and a better quality and accuracy of the forecasting activities (Roßmann et al., 2018). A particular application of BD for forecasting purposes is offered by Li and Wang (2017). Focusing on the fresh food chain and on BD collected through a network of sensors and RFID technologies, the authors propose a dynamic pricing strategy able to predict the residual shelf life of products at any stage of the SC.

Finally, BDA can be used for developing an environmentally sustainable SC strategy. El-Kassar and Singh (2019) prove that BD-based predictive analysis tools indirectly influence the competitive advantage by facilitating green innovation practices. Gružauskas et al. (2018) introduce a logistics network model for the food SC, based on Industry 4.0
technologies, which incorporates the optimal distribution strategy capable of minimising the trade-off between sustainability (reduction of CO₂ emissions) and competitiveness (reduction of transport costs). Zhang et al. (2018) developed an analytical framework that combines BDA with traditional methods for energy consumption analysis to examine and solve energy waste problems and, therefore, increase the competitiveness of energy-intensive manufacturing companies.

4.2.2 Red cluster: Big data, personalisation and co-creation strategies. The red cluster includes contributions that underline how BD provides information and knowledge regarding the needs, interests and behaviours of individual customers. They, therefore, encourage the use of BDA to personalise marketing strategies, customise and co-create innovation and new product development strategies, as well as develop effective business model innovation strategies. Quinn et al. (2016) claim that data manipulation, usually attributed to chief data officers or external digital agencies, and the formulation of marketing strategies, for which the marketing department is responsible, should be performed in a complementary and collaborative way. In doing so, the digital vision and marketing approaches can mutually reinforce each other and help manage the growing complexity of the market. For example, using BDA, the firm is able to effectively analyse the heterogeneity of preferences within different market segments and thus better personalise its value proposition (‘one-to-one’ approach).

Several contributions refer to the opportunity of using customer-generated BD to determine new segmentation criteria, based on variables such as price sensitivity and customer engagement (Kumar et al., 2017), customer opinions regarding the relevance of certain product or service attributes (Ahani et al., 2019) and the degree of knowledge and familiarity towards the product or service (Taylor-West et al., 2018). The development of a clear segmentation strategy represents an essential precondition to identifying and satisfying consumer needs. This activity is positioned upstream of the innovation cycle, with respect to which BD can play a facilitating role in the adoption of open innovation (OI) strategies (Trabucchi et al., 2018) by triggering the creation of knowledge flows that cross company borders (Chesbrough and Bogers, 2014). As a matter of fact, the company has the opportunity to use the knowledge extracted from multi-source data, especially User-Generated Big Data (UGBD), to optimise and speed up the internal innovation process (inbound OI) and the external diffusion and exploitation process (outbound OI). There are two literature streams that interpret the different roles played by users in supporting the development of business innovations: the user-centred innovation (UCI) approach and the user-driven innovation (UDI) approach (Trabucchi et al., 2018).

The UCI approach implies that the company exploits the insights deriving from the mere observation of the behaviours, opinions and needs expressed by customers during the use of products and services for new product development activities (Trabucchi et al., 2018). In this regard, BDA represent a more effective alternative tool compared to traditional methods such as interviews, focus groups and applied ethnography because they allow the company to collect several information spontaneously generated by users (Bendle and Wang, 2016; Qi et al., 2016), benefiting from a low cost and a high replicability.

Using the UDI approach, the company develops and prototypes new products in collaboration with individual customers (Trabucchi et al., 2018). UGBD can foster the effectiveness of the UDI approach because it can provide valuable information to sustain the ideas generated by the lead users, enrich user toolkits with context-related information and even support crowdsourcing platforms. The customer engagement model proposed by Kunz et al. (2017) helps to understand how UGBD can contribute to value co-creation. By using UGBD for the UCI approach, firms can exploit the online content freely generated by customers without their awareness. However, using UGBD for the UDI approach, companies can develop a ‘real collaboration’ because the user offers his ideas directly and consciously to the company, favouring the establishment of value co-creation processes.
Such collaboration usually takes place within dedicated online communities, where customer-generated BD of different nature (i.e. transactional, communication, participative and transboundary) and the digital platforms specifically made available by the company for its collection are transformed into cooperative assets capable of bringing benefits in a bilateral and stable manner (Xie et al., 2016). For instance, Buhalis and Sinarta (2019) highlight how the information exchange between the firm and the customers increases the opportunity to dynamically co-create services and experiences that are perceived as current and attractive by the consumer (‘nowness’).

Trabucchi et al. (2017) identify three main strategies for exploiting BD in the context of the so-called multi-sided platforms (i.e. markets in which the providers of goods or services act as intermediaries in the interaction between two or more groups of users). The first, ‘enhanced advertising’ is a strategic option by which a company uses consumer data to propose highly contextualised advertising messages tailored on user preferences. The second ‘e-ethnography’ is a strategy by which companies consider data relating to consumer habits, needs and relations as ‘by-products’ functional to the improvement of its core products and services and even as a final innovative output capable of automatically strengthening the corporate value proposition (Trabucchi and Buganza, 2019a). Lastly, in the third strategy, ‘data trading’ user data is directly sold to a third party, thus becoming a revenue-generating asset itself. The variety of strategic options enabled by UGBD makes their use capable of not only increasing the effectiveness and efficiency of product and service development and improvement but also triggering business model innovations, because of their significant impact on value creation, value appropriation and value delivery mechanisms (Sorescu, 2017; Trabucchi and Buganza, 2019b). The disclosure of the several opportunities that can be achieved through BD exploitation leads to consider the knowledge extracted from it as an important enabler (and not only a mere supporter) of firms’ value creation processes.

4.2.3 Blue cluster: Big data, strategic planning and strategic value creation pathways. This cluster groups the contributions that analyse the impact of BD on strategic planning processes and outlines the strategic paths through which firms can convert their BDAC into value.

With reference to the strategy-making context, Constantiou and Kallinikos (2015) highlight how the randomness, heterogeneity, updatability, lack of structure and the trans-semiotic and agnostic nature that distinguish BD significantly impact the assumptions on which the strategic formulation process is based. On the one hand, these characteristics lead to questioning the traditional top-down and deductive approaches of data collection and use, based on cognitive schemes outlined a priori in favour of bottom-up and inductive procedures extracting information from BD in a de-contextualised manner, so as to satisfy a variety of strategic purposes identified on the spot. On the other hand, they diminish the relevance of long-term forecasting approaches by facilitating a greater focus on the present (‘nowcasting’).

According to Mazzei and Noble (2017), in the strategic planning context, BD can be exploited to solve the problems related to the traditional activities of the value chain more effectively (‘data as a tool’), to create industries based on the sale of data and software for data management (‘data as an industry’) or to inform company strategies through the countless market opportunities identifiable through BD analysis (‘data as a strategy’). By explicitly adopting the ‘data as a strategy’ perspective, Gnizy (2019) demonstrates how BDA can influence some strategic orientations pursued by international companies and consequently their performance. Specifically, they can improve the engagement of existing customers and the acquisition of new ones, because of the greater understanding of their needs and desires (market orientation); they can continuously provide new transparent and reliable knowledge to support the company’s propensity to take risky and innovative decisions (entrepreneurial orientation) and they can finally strengthen a company learning
efforts by allowing to use the knowledge extracted from BD in a more effective way (learning orientation). Furthermore, using an opposite perspective, O’Connor and Kelly (2017) find that the strategic orientation acts as an enabler of the organisation’s readiness to effectively exploit the insights deriving from large datasets.

Several contributions belonging to this cluster focus on the strategic value creation paths that can be enabled by using BDA within the firm. Wang et al. (2018) develop a BDA-enabled transformation model that illustrates how the presence in the company of widespread IT capabilities and functionalities enables different combinations of organisational change practices directed to improve the company’s ability to create value. Elia et al. (2019) propose a multidimensional framework that identifies different types of value directions (i.e. informational, transactional, transformational, strategic and infrastructural) that can be pursued through the adoption of the BD paradigm.

In developing his own BD-based conceptual model of value creation, Grover et al. (2018) consider several theories: resource-based view (RBV), dynamic capabilities view (DCV), IT-strategy alignment theory and absorptive capacity theory. Following the logic of the RBV, the attributes of heterogeneity and immobility (i.e. the difficult availability for other companies) that characterise BD resources are by themselves functional to the value generation. In this regard, Roden et al. (2017) and Cheah and Wang (2017) consider BD as a precious and inimitable form of information resource that provides the necessary knowledge to seize the opportunities for incremental and radical innovation of operations models and business models respectively. According to DCV, the value of BDA increases when opportunities can be identified and exploited through the flexible reconfiguration of resources and value creation mechanisms, especially in the presence of changing environmental conditions. In this connection, Prescott (2014) believes that the competitive advantage achieved because of the ownership of valuable, rare, inimitable and non-replaceable resources is difficult to maintain over time if the company fails to avert their transformation into core rigidities (i.e. DCV). Specifically, as proven in the studies of Córte-Real et al. (2017, 2019), BDAC, being functional for the collection of data, information and knowledge in real-time, represent fundamental dynamic capabilities for the optimisation of company resources and operating routines. They, in turn, strengthen other dynamic capabilities (e.g. organisational agility), with positive relapses on the company competitiveness and ability to create value. Furthermore, the IT-strategy alignment theory suggests that the efficiency and effectiveness achievable using BDA can be strengthened by maintaining a certain consistency between strategy, resources, capabilities, processes and corporate governance practices (Akter et al., 2016). Finally, Grover et al. (2018) consider the perspective of the absorptive capacity theory (i.e. a firm’s capability to recognise, assimilate and exploit the value of new external knowledge) and outline how BD resources and capabilities allow firms to identify valuable external knowledge emerging from data that can be transformed into internal knowledge useful for innovating and adopting effective competitive strategies.

4.2.4 Green cluster: Big data and knowledge management. The green cluster can be considered, by position and content, a ‘bridge’ connecting the three clusters previously analysed. It collects studies that highlight how BDA support KM strategies. Information extracted from BD can be converted into valuable knowledge to be exploited and shared inside and outside the organisation. Companies increasingly feel the need to redefine their KM systems to make them capable of managing and integrating the multi-faceted and complex data available in a dynamic and transparent manner (Intezari and Gressel, 2017). Furthermore, BD is expected to revolutionise the entire field of KM by questioning traditional theoretical perspectives (e.g. the ‘data-information-knowledge continuum’) and therefore impacting on the very nature of decision-making processes (which is increasingly becoming a function of predictive modelling rather than a priori assumptions; Tian (2017)).
Olivo et al. (2016) propose a framework for the implementation of organisational learning models based on BD management principles. They highlight how incorporating BD in KM systems allows improving the quality and mitigating the risks of decision-making. In the same direction, the Big Data/Analytics-Knowledge Management model proposed by Pauleen and Wang (2017) explains how the use of BDA fosters and is in turn fuelled by the existing organisational knowledge. In particular, after identifying the reasons why it is necessary to collect and analyse data, on the one hand, business analysts use the available ‘contextual knowledge’ (i.e. the human knowledge and experience accumulated in the organisation) to select the most appropriate BDA to extract useful insights. On the other hand, they use these insights to solve pre-existing problems or formulate new strategies aimed to pursue sustainable competitive advantage (Harlow, 2018). Festa et al. (2018) advise firms characterised by ‘structural’ ambidexterity (i.e. which use dual organizational structures and strategies to differentiate efforts towards exploitation and exploration, as in the case of big pharma, which is naturally oriented to innovate rapidly and efficiently while still controlling risks and current sales), to adopt knowledge process standardisation as the main coordination mechanism for managing ‘big knowledge’ to simultaneously strengthen the exploitation of current activities and the exploration of future opportunities. Osuszek et al. (2016) overcome the perspective of business process management, which considers the single processes in a static and defined way, to adopt the adaptive case management (ACM) perspective and oriented to the timely and dynamic modification of business processes through a continuous experimentation of shared knowledge at an organisational level. The authors state that the dynamic ACM systems incorporating BD, being able to provide accurate and updated information regarding single business processes, facilitate the automation and optimisation of decision-making and the adoption of evidence-based approaches that are less dependent on managerial intuition. Nevertheless, the benefits associated with Decision Support Systems (DSS) powered by BD are not entirely foolproof. In this regard, Aversa et al. (2018) believe that the characteristics of the social, physical and technical environment, the distribution of decision-making activities among individuals and corporate artefacts and the performativity of DSS models may negatively influence the assumptions and methods of data-driven decision-making in organisations.

The possibility to effectively incorporate BD into corporate KM systems is connected to the company ability to develop reliable external knowledge networks, which in turn represent fundamental strategic means for the development of effective OI and co-creation strategies (Del Vecchio et al., 2018b). For example, knowledge-based organisations (e.g. museums) benefit from data-driven strategies if they manage to turn their physical and virtual environments into collaborative cultural ecosystems, in which users and other stakeholders participate actively to the creation and sharing of cultural contents through interactive learning experiences (Romanelli, 2018) while manufacturing firms can support new product development processes by introducing engagement online platforms where consumers spontaneously express their opinions and suggestions regarding purchased products (Troisi et al., 2018). Finally, some studies highlight how the presence of BD-enabled KM systems favours, in addition to collaborative innovation, greater inter-connection and inter-operability between partner companies of the same SC, thus allowing an effective joint operational and strategic planning (Buhalis and Leung, 2018).

Lastly, in the context of collaboration and knowledge sharing inside and outside the organisation, there are several contributions belonging to this cluster that focus on the opportunities offered by Web 2.0 tools. For instance, Arora and Predmore (2013) claim that social networks enable the creation of an open and transparent corporate environment where anyone can intervene to propose innovative ideas (concerning products and business processes). Such ideas are then selected and implemented by the organisation (i.e. ‘crowdsourcing’). Del Vecchio et al. (2018a) show how the exploitation of social BD allows tourism companies to configure data-driven business models, based on the exchange of local experiences and inspired by the principles of collaboration, networking
and crowdsourcing. Finally, Richard (2017) suggests that hotel chains may want to take advantage of UGBD available on social networks to create more customised services, tailored on customers’ needs and interests (‘micro-segmentation’).

5. Future research directions

The bibliometric analysis and literature review presented in the previous sections pave the way to several future research avenues (Tranfield et al., 2003) within each of the four thematic clusters (Figure 4).

Below we provide, as an example, a brief description of some of these future research avenues, starting with those concerning the green cluster. A first future research avenue could deepen the issue of BD impact on the structure and functioning of KM systems and, consequently, on business processes. This firstly requires a deeper examination of the

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**Figure 4** Big Data-strategy future research avenues

| FUTURE RESEARCH AVENUES | EXEMPLARY REFERENCES |
|-------------------------|----------------------|
| **Yellow cluster: Big data and supply chain strategy** |  |
| Deepen the role of big data in modifying information systems, processes, controls and decision-making practices characterising the supply chain | Brinch (2018); Tan et al. (2015) |
| Examine how the willingness and the different approaches to collaborate influence big data usage in the supply chain | Jimenez-Jimenez et al. (2019); Nagy et al. (2018); Richey et al. (2016) |
| Explore the Internet of Things applications that strengthen supply chain agility | Gružauskas et al. (2018); Li and Wang (2017) |
| Develop new big data techniques and creative uses to facilitate the forecasting and improve the sustainability of the supply chain | Fosso Wamba et al. (2017); Tan et al. (2015); Wang et al. (2016) |
| **Red cluster: Big data, personalisation and co-creation strategies** |  |
| Investigate the consequences deriving from the fragmentation of marketing activities on the collaboration and division of responsibilities between chief data officer and chief marketing officer on corporate competitiveness | Quinn et al. (2016); Sleep and Hulland (2018) |
| Examine the drawbacks of using UGBD in the implementation of ‘user-centred’ innovative strategies | Arthur and Owen (2019); Zhou et al. (2018) |
| Explore big data’s impact on the formulation and evaluation of co-creation engagement strategies | Kunz et al. (2017); Trabucchi et al. (2018); Xie et al. (2016) |
| Analyse the impact of data-driven open innovation strategies on firm value capture mechanisms | Cappa et al. (2019); Lepak et al. (2007); Trabucchi et al. (2017) |
| Investigate the approaches, alternatives and impacts of big data experimenting activities for business model innovation | Cheah and Wang (2017); Sorescu (2017); Trabucchi and Buganza (2019a) |
| **Blue cluster: Big data, strategic planning and strategic value creation pathways** |  |
| Deepen the impact of big data analytics on corporate governance processes and management’s ways of thinking for strategic planning purposes | Mazzei and Noble (2017); Merendino et al. (2018) |
| Conduct empirical research analysing the impact of big data on strategic orientations | Gnizy (2019); Zeng and Khan (2019) |
| Investigate risks, limits and drawbacks of using big data in strategy formulation | Constantiou and Kallinikos (2015); Roden et al. (2017) |
| Develop new models capable of opening the black box of value creation paths starting from big data analytics capabilities | Mamonov and Triantoro (2018); Wang et al. (2018) |
| **Green cluster: Big data and knowledge management** |  |
| Deepen the interrelationships between knowledge management processes and big data value chain phases | Harlow (2018); Landeta Olivo et al. (2016); Le Dihn et al. (2018); Paulsen and Wang (2017); Sumbal et al. (2017) |
| Examine the synergies and limitations of big data analytics compared to other decision-making methods and tools | Aversa et al. (2018); Xu et al. (2016) |
| Explore enablers (in terms of tools and organisational factors) capable of strengthening collaboration and knowledge sharing inside and outside the company | Moore (2017); Romanelli (2018) |
| Seek solutions to the openness paradox | Del Vecchio, Di Minin, et al. (2018); Sumbal et al. (2019) |
influence of BDA on information systems and technological platforms to investigate, for example, how much BDA adoption affects the company market sensing capacity (Richey et al., 2016) and how the tensions arising from the incorporation of external, mainly explicit, ‘big knowledge’ into organisational contextual knowledge (whose nature is mainly tacit) can be managed and limited (Pauleen and Wang, 2017; Sumbal et al., 2017). Secondly, the impact of BDA on business process management practices should be explored to identify the organisational structure configurations that are capable of optimising the coordination and interconnection between business processes and a profitable use of the insights extracted from BD through adequate DSS (Brinch, 2018). In addition, we invite future contributors to delve deeper and examine how KM systems can better leverage the potentiality of incorporating information deriving from disparate BD sources (e.g. enterprises, customers, competitors, partners and public data) to enhance existing value generation mechanisms or create new ones (Le Dinh et al., 2018).

The second future research direction concerns the knowledge sharing and collaboration strategies that could be enabled by BD. In particular, we consider it interesting to identify the factors encouraging different companies and individuals to share more or less confidential information (Nagy et al., 2018), as well as to analyse the variables that positively or negatively influence the results of collaboration with strategic partners such as the nature of widespread corporate culture (Moore, 2017) and the structure of existing power relationships (Richey et al., 2016). With reference to this last point, it could be interesting to investigate, for example, how the design of virtual collaborative environments (Romanelli, 2018) and the adoption of appropriate customer engagement approaches (Kunz et al., 2017) impact on the effectiveness of co-creation strategies based on knowledge sharing with businesses customers and consumers. Moreover, while the existing literature highlights the relevance of BD for the creation of value within the context of UDI strategies, it does not delve into the mechanisms through which firms can capture that value (Lepak et al., 2007). Further studies could therefore analyse the impact of data-driven OI strategies on firms’ future profits (Cappa et al., 2019) and aim to develop new business models capable of directly linking BD to value capture (Trabucchi et al., 2017). Finally, new empirical studies are needed to investigate the contribution of BDAC to incremental and radical innovation processes and see whether and to what extent this contribution is mediated by SC collaboration capabilities (Jimenez-Jimenez et al., 2019).

A further area of attention concerns the BDA impact, on the one hand, on corporate governance practices and management strategic culture and, on the other hand, on the division of managerial responsibilities. With reference to the first aspect, the challenges posed by BDA use require further investigations aimed at identifying the cognitive and dynamic capabilities that managers must possess to face these challenges successfully (Merendino et al., 2018), as well as the requirements and methods for the adoption of the ‘data as a strategy’ paradigm (Mazzei and Noble, 2017). Secondly, it is important to investigate the consequences of data proliferation and BDA adoption on the articulation of managerial responsibilities within the organisation. This can be done, for example, by investigating the most effective criteria to adopt for a successful collaborative relationship between chief data officers and chief marketing officers (Quinn et al., 2016) and by identifying innovative organisational learning models that allow to obtain an adequate degree of accountability concerning the strategy implementation process at each level of the company (Landaeta Olivo et al., 2016).

Lastly, a promising future research avenue concerns the risks, limits and drawbacks associated with the use of BDA to support strategic decisions, through which companies can convert BD into value. In the context of value co-creation strategies, further studies are needed to investigate new ways to formulate effective OI strategies considering both consumer privacy and company’s intellectual property defence (Del Vecchio et al., 2018b). For instance, it could be interesting to investigate causes and effects of uncontrolled external BD and knowledge sharing and which variables and instruments could help to limit
strategic knowledge leakage that would result (Sumbal et al., 2019). With regard to UCI strategies, it may be appropriate to investigate the implications related to the phenomenon of ‘overresponding’, i.e. the company tendency to ‘excessively’ respond to customer requests through continuous product or service innovations (Zhou et al., 2018). Finally, future researches should explore remedies and alternatives to an excessively ‘mechanical’ BDA application, which can sometimes return an overly simplified image of reality, thus limiting a conscious strategic planning implementation (Constantiou and Kallinikos, 2015).

6. Conclusions

This study proposes a mapping and a systematisation of the big data-business strategy research field through a bibliometric analysis and a systematic literature review. Four thematic clusters have been discovered. The first three clusters concern the following topics: big data and supply chain strategy; big data, personalisation and co-creation strategies and big data, strategic planning and strategic value creation pathways. The last cluster, which deals with the relationship between big data and knowledge management, represents, by position and content, a ‘bridge’ that brings together the three other clusters. Based on the authors’ knowledge, this is the first study to systematise and discuss the literature concerning the relationship between these two fields.

The bibliometric analysis and literature review presented in Section 4 allowed us to propose a tentative research agenda with several future research avenues.

This study has three main limitations. First, some steps of the selection process may have been biased by researchers’ interpretations. In line with the best methodological practices (Tranfield et al., 2003), this concern was addressed by performing a multiple human subject reading process whose reliability was confirmed by a Krippendorf’s alpha coefficient value greater than 0.80. Second, Scopus was used as reference database. This limitation was addressed by cross-checking the search string results on Web of Science and EBSCO Business Premier databases. Finally, the present study is mainly focused on profit firms. Therefore, future contributions could investigate the strategic implications of big data for public and non-profit organisations (Akoka et al., 2017; Jin et al., 2015).

We believe this research will prove useful to both scholars and managers. For the former, it offers a complete picture of the managerial literature on big data and firm strategy and identifies some interesting research gaps on which to base possible future studies. For the latter, it discloses the benefits of big data analytics implementation within existing organisational knowledge management systems in terms of supply chain optimisation, marketing and innovation strategies personalisation and more informed strategizing.

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