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Big Data and Innovation: The State of the Art and Future Research Directions

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ABSTRACT

Companies are increasingly aware of the benefits that can come from using big data. Of the various ways firms can make use of big data, in our research we have focused specifically on its use for innovation. As there are still many aspects that need to be clarified in this respect, our study addresses the following research question: how can big data be leveraged for innovation? Through a systematic literature review, we have inductively shown that three aspects emerge as critical in dealing with big data and innovation: (i) big data conceptualization; (ii) big data outcomes; and (iii) contingency factors. Around these aspects, we have mapped the current state of the art on big data and innovation, as well as highlighting interesting future research directions. On the whole, we have sought to advance scientific knowledge and provide useful insights for managers and research centers regarding the best way to leverage big data and innovation.

1 | Introduction

Digital transformation is changing the business environment and the way individuals and organizations interact (D'Ippolito et al. 2019; Crupi et al. 2020; Appio et al. 2021). This transformation presents organizations with many opportunities that they can leverage, including the possibility of easily collecting vast amounts of data, which leads to the accumulation of big data (Del Vecchio et al. 2018; Correani et al. 2020; Ceipek et al. 2021). There is no universally accepted definition of big data, but it can be identified as data so large and complex that it is difficult to process using traditional applications (Jin et al. 2015). According to Craig Mundie, former Chief Research and Strategy Officer at Microsoft, "*data are becoming the new raw material of business*" (Bai et al. 2016). It has been estimated that 149 zettabytes of data had been created as of 2024, and this value is expected to increase in the coming years (Statista 2024).

Big data has been found to bring many benefits to organizations. Previous literature has emphasized the various opportunities that big data provides, ranging from the improvement of daily operations within firms and supply chains as a whole (Etzion and Aragon-Correa 2016; Tiwari et al. 2018) to enhanced budgeting and marketing decisions (Wamba et al. 2017; Cappa et al. 2021), the advancement of planning assessment (Boeing 2021), more effective innovation activities (Bharadwaj and Noble 2017; Rindfleisch et al. 2017; Sorescu 2017; Troilo et al. 2017), improved technology transfer (da Silva et al. 2019), and, more generally, the enhancement of overall firm performance (Cappa et al. 2021; Pedota 2023). Thus far, research has mainly focused on the benefits generated by big data, overlooking—with few exceptions (e.g., Ghasemaghaei and Turel 2020; Cappa et al. 2021; Tamvada et al. 2022; Mortati et al. 2023)—the fact that there are also drawbacks associated with big data, like costs for database creation and management, privacy and security issues, insurance costs to protect against breaches, and the risk of being overwhelmed by the information available.

Due to the complexities, the benefits, and the drawbacks associated with big data, we contend that the focus of studies seeking to advance understanding of big data should be on one specific business function at a time. A literature review mapping the current state of scholarship and delineating possible future research directions, focused on big data in a specific business area, can be extremely useful for a wide audience to identify the main outcomes achieved so far, to frame the phenomenon, and to structure a future research agenda. In fact, the majority of previous literature reviews regarding big data attempted to provide a systematization of existing findings regarding the possible impact for organizations without focusing precisely on a specific area within organizations (e.g., Sivarajah et al. 2017; Ardito et al. 2018; Elia et al. 2020; Wiener et al. 2020; Acciarini et al. 2023). In this research, in contrast, we focus on innovation in organizations by providing a far-ranging overview of innovative outcomes and big data. Indeed, recent transformations that characterize the external environment—like digital transformation and the advent of many new technologies—have encouraged and forced companies to consider innovation more than ever. In fact, according to 87% of managers enrolled in an MBA program at a leading university in Europe, interviewed by the authors,[1] when asked to consider the possible uses of big data, innovation was the most significant for their companies. Moreover, policymakers have recently highlighted the need to focus on big data and innovation, as in the case of the Organization for Economic Co-operation and Development (OECD), which recently called upon countries to develop and implement data-driven innovation for growth and well-being (OECD 2022).

Big data in relation to innovation has turned into an important emerging research area. However, thus far we have lacked a clear picture of the possible impact and outcomes that big data may have in the field of innovation, as was also highlighted in other recent studies (Coussement et al. 2017; Cappa et al. 2021). In addition, during a webinar with the European Central Bank in September 2022, the European Union vice-president emphasized the view that big data has a great potential for innovation that still has not been fully uncovered (Vestager 2022). Considering this array of aspects related to big data for innovation, there is a crucial need to comprehend the overall phenomenon in a more focused, cohesive, and articulated way so that organizations can properly implement it. Thus, to fill this gap, we addressed the following research question: *How can big data be effectively leveraged for innovation?*

To answer this question and to contribute to a more comprehensive understanding of the current state of studies on big data and innovation, a systematic literature review (SLR) was conducted. Being reproducible and transparent processes, SLRs have increasingly been adopted by scholars in all sectors, including management (Franco-Santos and Otley 2018; Nguyen et al. 2018; Ardito et al. 2022; Sandoval Hamón et al. 2024), because they make it possible to summarize the state of research by providing a "*descriptive analysis of the field*" (Tranfield et al. 2003, 12) as well as allowing the start of "*new journeys*" (Massaro et al. 2016, 24) by identifying promising areas for future research. Thus, the aim of this research is to gather, analyze and summarize contributions regarding big data and innovation. In particular, we focused on publications in top management journals in the period 2017–2023. To do so, we searched for the keyword "big data" on Scopus, only considering the top three levels of journals in the innovation field according to the 2021 ABS ranking. Finally, after eliminating non-pertinent papers, we obtained the sample of 160 publications considered in this study. By analyzing these papers, we inductively identified three main aspects that emerged as critical if we are to fully understand big data for innovation: (i) big-data conceptualization; (ii) big data outcomes; and (iii) contingency factors. Thanks to the examination of these aspects, it is possible to better grasp the role big data plays in innovation studies.

On the whole, the findings of this research advance knowledge on the phenomenon by highlighting the main factors that need to be considered when dealing with big data and innovation, present an integrated view of the literature published on the aspects mentioned above, and indicate possible relevant future research directions. In this way we advance scientific understanding and also provide advice for managers, research centers, and policymakers on how to leverage innovation through big data. The remainder of the paper is organized as follows: in Section 2 we report the background of our study; in Section 3 we delineate our research methods; in Section 4 we highlight the results of the analyses conducted; in Section 5 we discuss the findings obtained and illustrate possible future developments; and in Section 6 we illustrate our conclusions.

2 | Background

Advancements in information technology and digital technology have led to the emergence of the digital transformations that we have been experiencing in recent years (Appio et al. 2021; Ceipek et al. 2021). The business environment is adapting to new digital opportunities, and the general public is also increasing its digital literacy (Ceipek et al. 2021; Cappa 2022). One of the results of this digitalization is the heightened ability to create masses of information, constituting big data. Big data was born as a dichotomous negative concept when, in the 1990s, excessive amounts of information created issues at the National Aeronautics and Space Administration (NASA) due to the limited storage capabilities of the hard disk drives of the times, leading to the "*problem of big data*" (Cox and Ellsworth 1997, 1). From then on, big data was predominantly considered a binary concept (Müller et al. 2018; Huang et al. 2018), i.e., whether a company had it or not. However, recently it has become increasingly clear that there are many dimensions to big data. Indeed, compared to traditional datasets, the most common view considers big data to be characterized not only by high values of volume but also of velocity, variety, veracity, and value, constituting the so-called 5V framework (Jin et al. 2015; Kiani Mavi et al. 2019; Hughes and Ball 2020).

Moreover, although the initial connotation of big data was negative, now the common assumption accompanying big data is that it is only beneficial for organizations because it can generate information and insights that can be extremely valuable. Recent examples of this were provided by Tencent, which used customer information to develop a credit scoring system to optimize the delivery of loans (Nonninger 2018), and by General Electric, which used information from their power plants to improve their efficiency (Wamba et al. 2017). In other words, the majority of studies have so far focused on the advantages generated by big data and have overlooked the disadvantages. However, big data can also create significant costs for firms, as has increasingly been recognized by both scholars and managers. Indeed, big data implies costs for database creation and management (Cappa et al. 2021). In addition, resources have to be devoted to properly analyzing the information collected (Cappa et al. 2022). Moreover, there are also costs related to privacy and security issues linked to the data gathered (Ghasemaghaei and Turel 2020; Cappa et al. 2021). For instance, British Airways was recently fined for the data theft they experienced (Sandle 2019), while DigiNotar even went bankrupt after a data breach (Zitter 2011). As a consequence of these issues, companies are increasingly taking out insurance to reduce the risk of data breaches and consequent reputational damage (Brook 2019; Bag et al. 2021). Furthermore, the abundance of data may also reduce the quality of decisions (Janssen et al. 2017; Ghasemaghaei and Turel 2020), leading to *info obesity*—i.e., so much data that it cannot be processed and it instead becomes dysfunctional for innovation (Whitler 2018). Nevertheless, it has been contended that, given the proper conditions, the benefits of big data for organizations can outweigh the costs associated with it (Cappa et al. 2021). Thus, a fuller understanding of the effects of big data is still desirable.

Based on the above, we can see that big data is a very broad phenomenon. Thus, in order to achieve a deeper understanding of it, we need to focus on its application for a specific function within organizations. Given that innovations are increasingly crucial for companies to sustain their competitive advantage in today's turbulent context and quickly changing environment, in this study we specifically focus on big data for innovation. It has been shown that big data can accelerate the innovation process (Fosso Wamba 2017; Zhan et al. 2017), as well as facilitate the adaptation of innovations to complex situations and improve reaction to unstable conditions in order to satisfy a wide range of customers (Zhan et al. 2017). In addition, big data has been shown to favor technology transfer by allowing a smoother absorption and dissemination of new technologies thanks to the additional insights that can be achieved (da Silva et al. 2019). As a matter of fact, organizations using big data in their innovation processes have been shown to be more likely to beat their competitors in terms of revenue and efficiency (Sorescu 2017). However, our understanding of big data regarding the innovation function within organizations is far from complete. To this end, a literature review can be extremely useful. The few literature reviews that touched on big data and innovation in past years did not conduct broad overviews of this topic but rather focused on specific applications like open innovation, i.e., a distributed model of innovation with knowledge inflows and outflows across organizational boundaries (Bogers et al. 2017, 2019), on small- and medium-sized enterprises (SMEs) (Del Vecchio et al. 2018), technology emerging in supply chains (Huang et al. 2018), decision-making in the public sector (Di Vaio et al. 2022), digitalization strategies (Sestino et al. 2020; Fernández-Rovira et al. 2021), business model innovation (Acciarini et al. 2023) and artificial intelligence systems (Zeba et al. 2021). However, an updated review that considers big data and innovation from a broad and deep perspective is still lacking. For this reason, we have conducted an SLR on big data and innovation to highlight the main critical factors to be considered, to probe current knowledge on the topic, and to inspire future research.

Starting from an initial analysis of the publications considered in our SLR, we inductively identified three main aspects that we contend must be considered regarding big data and innovation. Based on this proposed framework, we map out the current state of knowledge to provide a clear picture of where we are research-wise, and we also highlight what else can be done in future research to enrich our understanding in this respect. In particular, when identifying possible areas that deserve further consideration, we adopted both a gap-spotting approach and a problematizing one. Both are very conducive to interesting and useful research on management, as highlighted by Alvesson and Sandberg (2013). In the following section, we provide details on our research methodology and on the steps in the SLR we conducted.

3 | Methodology

We conducted an SLR in order to analyze and summarize material on a single subject using predetermined eligibility criteria that ensure replicability (Tranfield et al. 2003; Adams et al. 2017; Palmatier et al. 2018; Khosravi et al. 2019). SLRs not only lead to knowledge growth in a specific domain, but they also allow researchers to identify promising areas for future studies (Nguyen et al. 2018; Secundo et al. 2021). Indeed, this research method has increasingly been adopted by scholars in all disciplines (Franco-Santos and Otley 2018; Nguyen et al. 2018; Ardito et al. 2022). Therefore, by using SLRs, it is possible to report what is known and not known (Atewologun et al. 2017; Okwir et al. 2018) and highlight which critical research directions are to be explored in future research.

We can describe our research strategy for this SLR in detail: "*to broaden the degree of reliability and replicability of this inquiry*" (Dagnino et al. 2021, 3). In this study, we considered publications between 2017 and 2023. The breadth and the recentness of the timeframe selected are in line with other studies that performed SLRs (Hillmann and Guenther 2021; Graessler et al. 2024). Moreover, this choice was also driven by the fact that the number of publications on big data rose dramatically in 2017 as a result of increasing interest in this phenomenon. More specifically, we focused on papers published in top journals to assess relevant contributions that might influence scholars, managers, and policymakers in their understanding and actions (McGovern 2014). Consequently, we relied on the 2021 edition of the Academic Journal Guide ("ABS list"), i.e., the ranking produced by the UK Association of Business Schools, to identify top journals. The ABS is a ranking based both on citation indicators and peer reviews among scholars, and it is widely accepted worldwide to identify top management journals (Atewologun et al. 2017; Franco-Santos and Otley 2018; Nguyen et al. 2018; Dean et al. 2019; Ciuchta et al. 2021; del Carmen Triana et al. 2024; Heucher et al. 2024; O'donnell et al. 2024). The journal list is organized in levels, i.e., 1, 2, 3, 4, and 4*, going from the lowest to the highest rank. In line with previous studies (Ferrigno et al. 2023), we describe the phases of our article research strategy in detail. As a first step, we searched for publications through the Scopus database (Centobelli et al. 2020; De Marchi et al. 2020; Ardito et al. 2022), using "big data" as the keyword and limiting documents to those published in English between 2017 and 2023; we found a total of 128,676 publications. We then filtered for 3, 4, and 4* ABS journals to focus on the most rigorous and relevant publications, as already done in previous research (Atewologun et al. 2017; Franco-Santos and Otley 2018; Nguyen et al. 2018; Dean et al. 2019; Saebi et al. 2019; Whittle et al. 2023), and this produced 3586 papers. We used the ABS ranking to limit our search to top publications rather than using the impact factor, which has, in contrast, been used by other authors with the same aim (Perri and Peruffo 2016; Müller and Kunisch 2018), because the advantage of this ranking is that it considers both citation indicators and scholars' qualitative evaluations, and also because it allows us to focus on specific areas of management. Thanks to this, we focused our attention on the 3, 4, and 4* journals pertaining to the category of "innovation" as per the 2021 ABS list[2] (i.e., *Research Policy*, the *Journal of Product Innovation Management, Industry and Innovation, R&D Management*, the *Journal of Technology Transfer, Technological Forecasting and Social Change*, and *Technovation*), and the number of published studies became 201. From this pool of papers, as a fourth step, we eliminated those that were "corrigendum," "literature reviews," and "editorials," and this produced a total of 176 documents. As a final step, we carefully checked the abstracts so that only articles properly pertaining to big data and innovation would remain in the sample (Marzi et al. 2024). The final sample included 160 papers, a size that is in line with other recent SLRs (Miller et al. 2018; Castro et al. 2020; Whittle et al. 2023; Park et al. 2024; Han et al. 2025). All the selection criteria reported above are summarized in Figure 1.

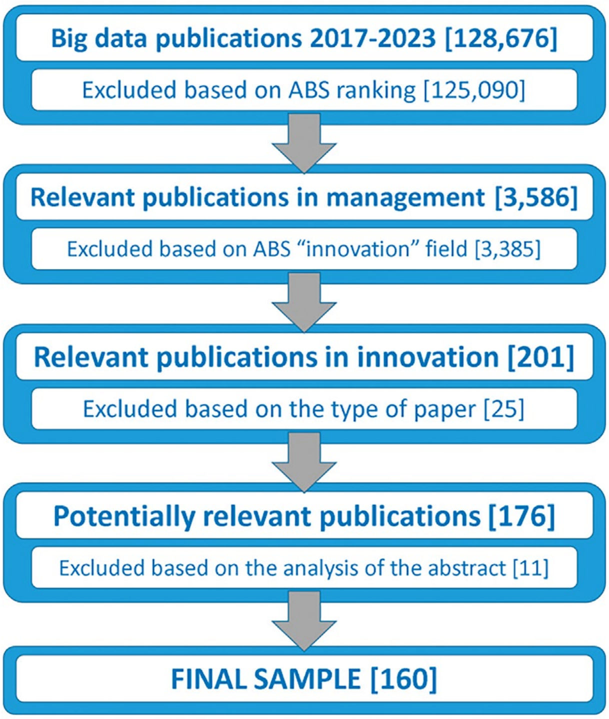

FIGURE 1 | Selection criteria for papers included in the analysis. [Colour figure can be viewed at wileyonlinelibrary.com]

The authors, who have experience with top-tier journal publishing on the topic of big data and innovation, as well as with the process of conducting literature reviews, carefully read the final articles selected through the process described above. Using an inductive approach (Raff et al. 2020; Shepherd et al. 2021) when reading these publications, the authors identified three crucial aspects that emerged as critical when dealing with big data and innovation. In particular, we identified similar attributes in the papers and recognized the underlying logic behind these similarities (Graessler et al. 2024). Starting from these aspects, the papers identified through the SLR were analyzed and mapped to provide an updated overview of the state of scholarly knowledge. In addition, future research directions worthy of investigation have also been highlighted regarding the above-mentioned aspects. When doing this, we adopted a gap-identification approach as well as a problematizing approach, which has been shown to be extremely useful in management to enrich understanding of a phenomenon with novel findings (Alvesson and Sandberg 2013). In this way, in addition to highlighting areas that deserve further consideration, we also "*come up with novel research questions through a dialectical interrogation of one's own familiar position, other stances, and the domain of literature*" (Alvesson and Sandberg 2013, 18). The articles were analyzed independently by the authors and the results were later merged. Consensus regarding the results applied to 95% of the publications examined during the first round. The few doubts remaining regarding 5% of the sample were resolved after a further round of discussion among the authors.

4 | Results

4.1 | Critical Aspects to Consider When Dealing With Big Data and Innovation

The themes that inductively emerged as being critical in the application of big data for innovations proved to be (i) big-data conceptualization, (ii) big data outcomes, and (iii) contingency factors. We contend that the attention of scholars, managers, and policymakers dealing with big data and innovation should be concentrated on these three aspects, which are summarized in a schematic framework in Figure 2. Details on the significance of each of the aspects are reported below.

Firstly, scholarship has increasingly recognized that big data can be identified not just based on a dichotomous option, i.e., whether an organization has it or not, but also on a multidimensional concept. Indeed, it is increasingly clear that big data is not limited to a high volume of information; instead, other dimensions should be considered. For instance, if companies have zettabytes of data about customers, but this data only includes a few items of information, like their age and city of residence, this may not constitute a case of big data. It could more properly become big data if these companies also had other items of information for each observation, such as gender, wages, and level of education. This would produce data variety, and if the data were collected almost in real time, i.e., possessing velocity, it would fit the 3V framework identified in the literature (Johnson et al. 2017; Blazquez and Domenech 2018; Wang et al. 2018). When veracity, i.e., the presence of efforts

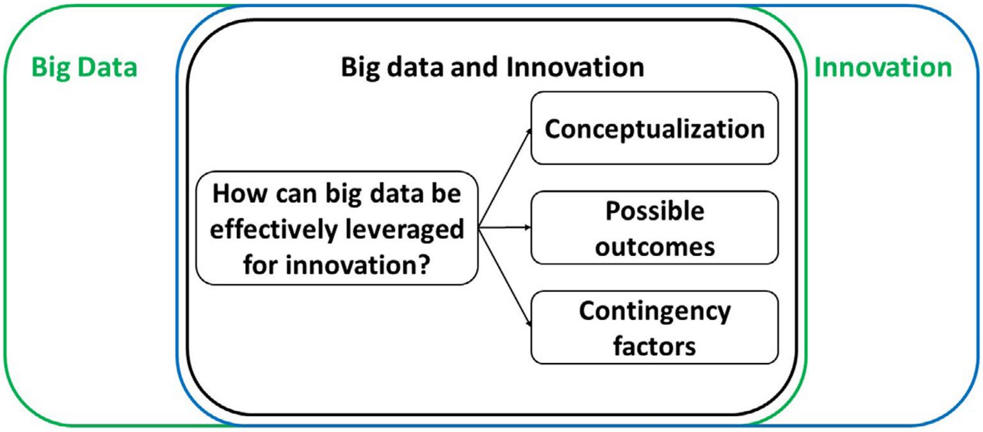

FIGURE 2 | Selection criteria for papers included in the analysis. [Colour figure can be viewed at wileyonlinelibrary.com]

undertaken by firms to have reliable insights, and value, i.e., meaningful information for the organization, are also considered, the 5V framework can be established (Jin et al. 2015; Cappa et al. 2021, 2022; Di Vaio et al. 2022). Consideration of the different dimensions leading to the various dimensional conceptualizations of big data, e.g., the widely used 3Vs and 5Vs, rather than simply a binary distinction of big data presence, is an important aspect to consider when dealing with its possible application to innovation. To achieve this aim, theoretical grounding also plays a crucial role. Indeed, when studying big data, certain theoretical lenses have already been employed and should be used further. In addition, to enrich understanding of the outcomes of big data, other theoretical perspectives may also be useful.

Secondly, understanding the possible outcomes was another critical aspect. In fact, researchers should not only consider and scrutinize benefits but also drawbacks, since the latter are often overlooked. Indeed, costs and risks need to be examined so that firms ensure that the advantages of big data outweigh the disadvantages. In addition, the impact of innovations driven by big data has been considered in relation to all three aspects of sustainability, i.e., not only economic but also environmental and social (Cappa et al. 2022; Morea et al. 2022). Given the pressing grand challenges society is facing today (D'Angelo et al. 2022, 2023; Cappa 2022; Collevecchio et al. 2024), there has, indeed, been increasing demand for innovations that benefit all three pillars of sustainability (Sauermann et al. 2020).

Thirdly, contingency factors appear to be vital in understanding how big data may be leveraged to innovate. Indeed, the type of innovation within the organization is also important in order to understand the uses that can be made of big data. For example, crucial aspects to consider are whether the firm using big data is focused on (1) radical or incremental innovations, i.e., whether the changes produced by the adoption of big data are actually substantial or marginal (Ritala and Hurmelinna-Laukkanen 2009; Kobarg et al. 2019); (2) disruptive rather than sustaining innovations, i.e., whether innovations can disrupt current products and services or support them (Reinhardt and Gurtner 2015; Del Vecchio et al. 2018); (3) architectural or component innovations, i.e., innovations that involve the overall design and the way in which parts interact or just a single piece (Lee and Veloso 2008; Albert and Siggelkow 2022); (4) modular or integral innovation, i.e., for products that involve several interacting pieces or those without any interface to communicate with other products (Chen and Liu 2005; Habib et al. 2020); or (5) a specific product, service, process, or business model type of innovation (Visnjic et al. 2016).

4.2 | Mapping the Literature

Based on the three aspects identified above, we dissected the corresponding results of our SLR as detailed in the following subsections and as also reported in Table 1.

4.2.1 | Big-Data Conceptualization

Concerning the conceptualization of big data, ranging from the initial dichotomous view to the more recent multidimensional perspective, the studies examined adopted different approaches. The majority of manuscripts, namely 89 studies, considered big data simply as being present or absent, i.e., as a binary variable (e.g., Urbinati et al. 2018; Chalvatzis et al. 2019; Zhang, Huang, et al. 2019; Gupta et al. 2021; Han and Trimi 2022; Kazancoglu et al. 2021; Cho et al. 2023). In contrast, other studies considered big data as being constituted by multiple dimensions. It has often been acknowledged that big data is connected with two dimensions, i.e., volume and velocity (Ghosh and Jana 2023) or volume and variety (Pedota 2023). Most studies, precisely 38 of them, viewed it as composed of three dimensions, i.e., the 3V framework, namely volume, variety, and velocity (e.g., Gupta et al. 2019; Ashaari et al. 2021; Kayabay et al. 2022; Li et al. 2022; Fukawa and Rindfleisch 2023). In addition, four studies added the dimensions of either veracity or value, leading to a 4V framework (LaBrie et al. 2018; Jabbour et al. 2019; Fernández-Rovira et al. 2021; Hassani et al. 2021). Moreover, 20 studies were based on the 5Vs by adding both the value and veracity dimensions (e.g., Hofmann et al. 2019; Shamim et al. 2020; Di Vaio et al. 2022; Rodríguez-Espíndola et al. 2022; Mortati et al. 2023). Additionally, two studies added the variability dimension, leading to 6Vs (Sheng et al. 2019; Kristoffersen et al. 2021), and finally, five studies described the more comprehensive 7V framework by also considering visualization (Rialti et al. 2019; Bag et al. 2021; Kamble et al. 2021; Boubaker

TABLE 1 | Map of the studies considered in this systematic literature review.

Paper details			Big-data conceptualization		Big-data outcomes			Contingency factors			
ID	**Authors and year**	**Journal**	**Dimensions**	**Theory used**	**Only benefits**	**Benefits & costs**	**Environmental & social sustainability**	**Radical & incremental**	**Disruptive & sustaining**	**Architectural, modular & component**	**Type of innovative outcome**
1	de Souza et al. (2021)	Technological Forecasting and Social Change	Binary	Resource-based view	X		X				Process
2	Kazancoglu et al. (2021)	Technological Forecasting and Social Change	Binary	Fuzzy theory	X		X				Process
3	Kamble et al. (2021)	Technological Forecasting and Social Change	7Vs	Stakeholder theory	X		X	Radical & incremental			Process
4	Chang (2018)	Technological Forecasting and Social Change	Binary	Social network theory	X						Process
5	Calış Duman and Akdemir (2021)	Technological Forecasting and Social Change	Binary		X						Process
6	Del Vecchio et al. (2019)	Technological Forecasting and Social Change	Binary	Simulation theory	X		X				Process
7	Huang et al. (2018)	Technological Forecasting and Social Change	Binary		X						
8	Chang (2021)	Technological Forecasting and Social Change	3Vs			X					Process
9	Abdel-Basset et al. (2021)	Technological Forecasting and Social Change	Binary	Neutrosophic theory	X				Disruptive		Process
10	Nguyen Dang Tuan et al. (2019)	Technological Forecasting and Social Change	Binary	Mindfulness-based reliability theory	X						Business Model
11	Huang and Liu (2021)	Technological Forecasting and Social Change	Binary	Humanizing experience theory			X		Disruptive		

(Continues)

TABLE 1 | (Continued)

Paper details			Big-data conceptualization		Big-data outcomes			Contingency factors			
ID	**Authors and year**	**Journal**	**Dimensions**	**Theory used**	**Only benefits**	**Benefits & costs**	**Environmental & social sustainability**	**Radical & incremental**	**Disruptive & sustaining**	**Architectural, modular & component**	**Type of innovative outcome**
12	Mahmood and Mubarik (2020)	Technological Forecasting and Social Change	Binary	Human capital	X			Radical & incremental			Process
13	von Hippel and Cann (2021)	Research Policy	Binary	User Innovation	X						
14	Rialti et al. (2019)	Technological Forecasting and Social Change	7Vs	Dynamic capabilities	X			Radical & incremental			
15	Shamim et al. (2020)	Technological Forecasting and Social Change	5Vs	Dynamic capabilities	X						Process
16	Awan et al. (2021)	Technological Forecasting and Social Change	Binary	Organizational learning	X						Process
17	Ashaari et al. (2021)	Technological Forecasting and Social Change	3Vs	Resource-based view	X	X					Process
18	Liu et al. (2018)	Technological Forecasting and Social Change	Binary	User Innovation	X						
19	LaBrie et al. (2018)	Technological Forecasting and Social Change	4Vs		X		X				Process
20	Iqbal et al. (2020)	Technological Forecasting and Social Change	3Vs	Emotion theory	X						Process
21	Wang et al. (2018)	Technological Forecasting and Social Change	3Vs		X						Process
22	Xie et al. (2021)	Technological Forecasting and Social Change	3Vs	Composition-based view	X						

(Continues)

TABLE 1 | (Continued)

Paper details			Big-data conceptualization		Big-data outcomes			Contingency factors			
ID	**Authors and year**	**Journal**	**Dimensions**	**Theory used**	**Only benefits**	**Benefits & costs**	**Environmental & social sustainability**	**Radical & incremental**	**Disruptive & sustaining**	**Architectural, modular & component**	**Type of innovative outcome**
23	Gupta et al. (2021)	Technological Forecasting and Social Change	Binary	Open innovation framework	X						
24	Johnson et al. (2017)	Journal of Product Innovation Management	3Vs	Dynamic capabilities and Organizational Learning				Radical & Incremental	Disruptive		Product and Service
25	Cappa et al. (2021)	Journal of Product Innovation Management	3Vs	Resource-based view		X					Product, Service, Process and Business Model
26	Chandy et al. (2017)	Journal of Product Innovation Management	3Vs		X		X				Product, Service, Process and Business Model
27	Basukie et al. (2020)	Technological Forecasting and Social Change	Binary		X						Process
28	Blazquez and Domenech (2018)	Technological Forecasting and Social Change	3Vs	Decision theory	X						Process
29	Modgil et al. (2021)	Technological Forecasting and Social Change	Binary	Stakeholder theory			X		Disruptive		Process
30	Akhtar et al. (2019)	R&D Management	Binary	Open Innovation framework	X						
31	Dubey et al. (2019)	Technological Forecasting and Social Change	3Vs	Dynamic capability	X		X				Process
32	Gupta et al. (2019)	Technological Forecasting and Social Change	3Vs	Stakeholder theory	X		X	Radical & incremental			Process

(Continues)

TABLE 1 | (Continued)

Paper details			Big-data conceptualization		Big-data outcomes			Contingency factors			
ID	Authors and year	Journal	Dimensions	Theory used	Only benefits	Benefits & costs	Environmental & social sustainability	Radical & incremental	Disruptive & sustaining	Architectural, modular & component	Type of innovative outcome
33	Choi and Chen (2021)	Technological Forecasting and Social Change	Binary		X						Process
34	Naccarato et al. (2018)	Technological Forecasting and Social Change	3Vs	Human capital	X						Service
35	Barchiesi and Fronzetti Colladon (2021)	Technological Forecasting and Social Change	Binary	Stakeholder theory	X						
36	Urbinati et al. (2018)	Technovation	Binary	Value creation and value capture	X				Disruptive & sustaining		Product, Service, Process and Business Model
37	Sorescu (2017)	Journal of Product Innovation Management	3Vs	Value creation and value capture	X		X	Radical	Disruptive		Product, Service, Process and Business Model
38	Boeing and Wang (2021)	R&D Management	Binary	Open innovation framework	X						
39	Rippa and Secundo (2019)	Technological Forecasting and Social Change	Binary								Process
40	Zhang, Huang, et al. (2019)	Technological Forecasting and Social Change	Binary								
41	Han et al. (2021)	Technological Forecasting and Social Change	Binary	Gratification theory	X				Disruptive		
42	Chiang and Yang (2018)	Technological Forecasting and Social Change	Binary		X						Product and Service

(Continues)

TABLE 1 | (Continued)

Paper details			Big-data conceptualization		Big-data outcomes			Contingency factors			
ID	**Authors and year**	**Journal**	**Dimensions**	**Theory used**	**Only benefits**	**Benefits & costs**	**Environmental & social sustainability**	**Radical & incremental**	**Disruptive & sustaining**	**Architectural, modular & component**	**Type of innovative outcome**
43	Lamba and Singh (2019)	Technological Forecasting and Social Change	3Vs		X						Process
44	Chen et al. (2018)	Technological Forecasting and Social Change	Binary	Opinion leadership							Product and Service
45	Chaudhary et al. (2021)	Technological Forecasting and Social Change	3Vs			X					Product and Service
46	Liu et al. (2019)	Technological Forecasting and Social Change	5Vs	Big data theory	X						Product and Service
47	Kayser and Blind (2017)	Technological Forecasting and Social Change	Binary						Disruptive		Process
48	Yakubu and Kwong (2021)	Technological Forecasting and Social Change	Binary	Fuzzy theory	X						Process
49	Shan et al. (2020)	Technological Forecasting and Social Change	Binary	Resource-based view	X						Product and Service
50	van den Broek and van Veenstra (2018)	Technological Forecasting and Social Change	Binary	Organization theory		X			Disruptive		Process
51	El-Kassar and Singh (2019)	Technological Forecasting and Social Change	3Vs	Resource-based view	X		X				Product and Service
52	Kim and Geum (2021)	Technological Forecasting and Social Change	Binary	Fuzzy theory	X		X				Process
53	Dotsika and Watkins (2017)	Technological Forecasting and Social Change	Binary	Network theory	X				Disruptive		Process

(Continues)

TABLE 1 | (Continued)

Paper details			Big-data conceptualization		Big-data outcomes			Contingency factors			
ID	**Authors and year**	**Journal**	**Dimensions**	**Theory used**	**Only benefits**	**Benefits & costs**	**Environmental & social sustainability**	**Radical & incremental**	**Disruptive & sustaining**	**Architectural, modular & component**	**Type of innovative outcome**
54	Yu, He, and Zhao (2021)	Technological Forecasting and Social Change	Binary	Game theory	X		X				Product and Service
55	Llopis-Albert et al. (2021)	Technological Forecasting and Social Change	Binary	Fuzzy theory	X				Disruptive		Business model
56	Tan and Zhan (2017)	R&D Management	3Vs		X						
57	Coussement et al. (2017)	Journal of Product Innovation Management	3Vs	Social exchange theory & social identity theory	X						
58	Yadegaridehkordi et al. (2018)	Technological Forecasting and Social Change	5Vs	Fuzzy theory	X						Process
59	Mariani and Nambisan (2021)	Technological Forecasting and Social Change	3Vs	Resource-based view	X				Disruptive		Process
60	Sestino et al. (2020)	Technovation	3Vs		X		X		Disruptive		Product, Service, Process and Business model
61	Hofmann et al. (2019)	Technological Forecasting and Social Change	5Vs	Network theory	X						Process
62	Julsrud and Krogstad (2020)	Technological Forecasting and Social Change	Binary			X					Process
63	Irwin et al. (2021)	Research Policy	Binary	Institutional -theory	X						
64	Kiani Mavi et al. (2019)	Technological Forecasting and Social Change	5Vs		X		X				Process

(Continues)

TABLE 1 | (Continued)

Paper details			Big-data conceptualization		Big-data outcomes			Contingency factors			
ID	Authors and year	Journal	Dimensions	Theory used	Only benefits	Benefits & costs	Environmental & social sustainability	Radical & incremental	Disruptive & sustaining	Architectural, modular & component	Type of innovative outcome
65	Troilo et al. (2017)	Journal of Product Innovation Management	3Vs	Structural contingency	X			Radical			Product, Service and Process
66	Belhadi et al. (2021)	Technological Forecasting and Social Change	Binary	Supply chain resilience	X						Process
67	Arora et al. (2020)	Journal of Technology Transfer	Binary	Dynamic capabilities		X		Radical	Disruptive		Product
68	Chen (2018)	Technological Forecasting and Social Change	3Vs			X			Disruptive		Process
69	Zhang, Du, et al. (2019)	Technological Forecasting and Social Change	Binary	Interpersonal behavior	X						Product and Service
70	Yue et al. (2021)	Technological Forecasting and Social Change	Binary						Disruptive		Process
71	Kiani Mavi and Kiani Mavi (2021)	Technological Forecasting and Social Change	5Vs		X			Radical & incremental			Process
72	Tahi et al. (2021)	Technovation	Binary	Network theory	X		X				Product, Service, Process and Business model
73	Aykroyd et al. (2019)	Technological Forecasting and Social Change	3Vs		X						
74	Zhang, Yan, and Guan (2019)	Technological Forecasting and Social Change	Binary	Network theory	X						Product and Service

(Continues)

TABLE 1 | (Continued)

Paper details			Big-data conceptualization		Big-data outcomes			Contingency factors			
ID	**Authors and year**	**Journal**	**Dimensions**	**Theory used**	**Only benefits**	**Benefits & costs**	**Environmental & social sustainability**	**Radical & incremental**	**Disruptive & sustaining**	**Architectural, modular & component**	**Type of innovative outcome**
75	Akter et al. (2020)	Technological Forecasting and Social Change	Binary	Resource-based view	X						Product and Service
76	Walton and Nayak (2021)	Technological Forecasting and Social Change	Binary			X			Disruptive		
77	Yu, Zhao, et al. (2021)	Technological Forecasting and Social Change	3Vs	Organizational information processing theory	X						Product and Service
78	Bag et al. (2021)	Technological Forecasting and Social Change	7Vs	Institutional theory and resource-based view		X	X				Process
79	Kayser and Shala (2020)	Technological Forecasting and Social Change	Binary			X					Process
80	Shen et al. (2019)	Technological Forecasting and Social Change	Binary	Bayesian conjugate pair theory	X		X				Product and Service
81	Hughes and Ball (2020)	Technological Forecasting and Social Change	5Vs		X						Process
82	Chalvatzis et al. (2019)	Technological Forecasting and Social Change	Binary		X		X	Radical innovation		Architectural innovation	Process
83	Sohrabi and Khalilijafarabad (2018)	Technological Forecasting and Social Change	Binary			X					
84	Soni et al. (2021)	Technological Forecasting and Social Change	Binary		X		X				Process

(Continues)

TABLE 1 | (Continued)

Paper details			Big-data conceptualization		Big-data outcomes			Contingency factors			
ID	**Authors and year**	**Journal**	**Dimensions**	**Theory used**	**Only benefits**	**Benefits & costs**	**Environmental & social sustainability**	**Radical & incremental**	**Disruptive & sustaining**	**Architectural, modular & component**	**Type of innovative outcome**
85	Sheng et al. (2019)	Technological Forecasting and Social Change	6Vs	Big data theory	X						Process
86	Zeba et al. (2021)	Technological Forecasting and Social Change	Binary		X						
87	Jun et al. (2018)	Technological Forecasting and Social Change	Binary	Network theory	X						Process
88	Wang et al. (2020)	Technological Forecasting and Social Change	5Vs								
89	Meadows et al. (2021)	Technological Forecasting and Social Change	3Vs		X	X			Disruptive		Process
90	Ibrahim et al. (2021)	Technological Forecasting and Social Change	5Vs	Agency theory and stakeholder theory		X					Process
91	Fernández-Rovira et al. (2021)	Technological Forecasting and Social Change	4Vs			X			Disruptive		
92	Manita et al. (2020)	Technological Forecasting and Social Change	3Vs	Agency theory and stakeholder theory		X					Process
93	Roßmann et al. (2018)	Technological Forecasting and Social Change	3Vs	Organizational information processing theory	X						Process
94	Benzidia et al. (2021)	Technological Forecasting and Social Change	3Vs	Organizational information processing theory	X		X				Process
95	AlNuaimi et al. (2021)	Technological Forecasting and Social Change	5Vs	Resource orchestration theory	X		X				Product and Service

(Continues)

TABLE 1 | (Continued)

Paper details			Big-data conceptualization		Big-data outcomes			Contingency factors			
ID	Authors and year	Journal	Dimensions	Theory used	Only benefits	Benefits & costs	Environmental & social sustainability	Radical & incremental	Disruptive & sustaining	Architectural, modular & component	Type of innovative outcome
96	Hassani et al. (2021)	Technological Forecasting and Social Change	4Vs		X						
97	Čábelková et al. (2021)	Technological Forecasting and Social Change	5Vs		X						
98	Malyy et al. (2021)	Technological Forecasting and Social Change	Binary	Configuration theory	X						Product and Service
99	Kwon et al. (2018)	Technological Forecasting and Social Change	Binary		X						Process
100	Kristoffersen et al. (2021)	Technological Forecasting and Social Change	6Vs	Resource-based view	X		X				Process
101	Han and Trimi (2022)	Technological Forecasting and Social Change	Binary			X					Process
102	Liu et al. (2021)	Technological Forecasting and Social Change	Binary		X						Process
103	Jabbour et al. (2019)	Technological Forecasting and Social Change	4Vs	Stakeholder theory		X	X				Process
104	Resce and Maynard (2018)	Technological Forecasting and Social Change	3Vs		X						Product and Service
105	Soni et al. (2022)	Technological Forecasting and Social Change	Binary	Fuzzy set theory		X	X				Process
106	Wilson et al. (2023)	Technological Forecasting and Social Change	Binary		X						

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TABLE 1 | (Continued)

Paper details			Big-data conceptualization		Big-data outcomes			Contingency factors			
ID	**Authors and year**	**Journal**	**Dimensions**	**Theory used**	**Only benefits**	**Benefits & costs**	**Environmental & social sustainability**	**Radical & incremental**	**Disruptive & sustaining**	**Architectural, modular & component**	**Type of innovative outcome**
107	Ghosh and Jana (2023)	Technological Forecasting and Social Change	2Vs		X						
108	Tamvada et al. (2022)	Technological Forecasting and Social Change	Binary			X					
109	Rodríguez-Espíndola et al. (2022)	Technological Forecasting and Social Change	5Vs	Institutional theory, Resource-based-view, and Technology acceptance.		X			Disruptive		
110	Chatterjee et al. (2023)	Technological Forecasting and Social Change	Binary	Resource-based view and Dynamic capabilities	X						Process
111	Rikap (2022)	Research Policy	Binary	Network theory e Intellectual monopoly	X					Modularity	Process
112	Zhukov et al. (2022)	Technological Forecasting and Social Change	Binary	Probability theory	X						Process
113	Boubaker et al. (2023)	Technological Forecasting and Social Change	7Vs		X						Process
114	Qi et al. (2023)	Technological Forecasting and Social Change	3Vs	Fuzzy theory	X						
115	Weerasinghe et al. (2022)	Technological Forecasting and Social Change	5Vs	Social representation theory		X					Process
116	Pedota (2023)	Research Policy	2Vs	Dynamic capabilities	X						Business model

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TABLE 1 | (Continued)

Paper details			Big-data conceptualization		Big-data outcomes			Contingency factors			
ID	**Authors and year**	**Journal**	**Dimensions**	**Theory used**	**Only benefits**	**Benefits & costs**	**Environmental & social sustainability**	**Radical & incremental**	**Disruptive & sustaining**	**Architectural, modular & component**	**Type of innovative outcome**
117	Gao et al. (2023)	Technological Forecasting and Social Change	5Vs		X		X				Product
118	Plantec et al. (2023)	Technovation	Binary	Knowledge search	X				Disruptive		Process
119	Xuan (2022)	Technological Forecasting and Social Change	Binary	Fuzzy set theory	X						
120	Basile et al. (2023)	Technovation	Binary		X						Process
121	Wang et al. (2022)	Technological Forecasting and Social Change	Binary	Resource dependency	X						
122	Tseng et al. (2022)	Technological Forecasting and Social Change	Binary		X						Product
123	Mortati et al. (2023)	Technovation	5Vs			X					Process
124	Di Vaio et al. (2022)	Technological Forecasting and Social Change	5Vs	Institutional theory, Resource-based view and Ambidexterity theory	X		X				Business model
125	Kayabay et al. (2022)	Technological Forecasting and Social Change	Binary		X		X				Process
126	Sariyer et al. (2023)	Technological Forecasting and Social Change	Binary	Big-data analytics capabilities	X						Process
127	Hossain et al. (2023)	Technological Forecasting and Social Change	Binary	Resource-based view	X						Service

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TABLE 1 | (Continued)

Paper details			Big-data conceptualization		Big-data outcomes			Contingency factors			
ID	Authors and year	Journal	Dimensions	Theory used	Only benefits	Benefits & costs	Environmental & social sustainability	Radical & incremental	Disruptive & sustaining	Architectural, modular & component	Type of innovative outcome
128	Razzaq and Yang (2023)	Technological Forecasting and Social Change	Binary		X		X		Disruptive		Service
129	Jaung (2022)	Technological Forecasting and Social Change	Binary	Random utility theory	X						
130	Choi and Park (2022)	Technological Forecasting and Social Change	3Vs	Resource-based view	X		X				Service
131	Mariani et al. (2023)	Technological Forecasting and Social Change	5Vs		X						Service
132	Saeed et al. (2022)	Technological Forecasting and Social Change	3Vs	Resource-based view and Organizational legitimacy	X						Service
133	Sharma et al. (2023)	Technovation	Binary	Resource-based view and Dynamic capabilities theory	X		X		Disruptive		Business model
134	Fukawa and Rindfleisch (2023)	Journal of Product Innovation Management	3Vs	Resource-based view and dynamic capabilities theory	X		X				Process
135	Cuomo et al. (2022)	Technological Forecasting and Social Change	Binary	Service dominant	X						Process
136	Corallo et al. (2023)	Technological Forecasting and Social Change	3Vs			X					Process
137	Li et al. (2022)	Technological Forecasting and Social Change	3Vs		X						Service

(Continues)

TABLE 1 | (Continued)

Paper details			Big-data conceptualization		Big-data outcomes			Contingency factors			
ID	Authors and year	Journal	Dimensions	Theory used	Only benefits	Benefits & costs	Environmental & social sustainability	Radical & incremental	Disruptive & sustaining	Architectural, modular & component	Type of innovative outcome
138	Bag et al. (2023)	Technological Forecasting and Social Change	5Vs	Ethical theory of organizing and Stakeholders theory		X	X				
139	Tiberius et al. (2022)	Technological Forecasting and Social Change	Binary		X						Process
140	Gandhi and Kar (2022)	Technological Forecasting and Social Change	Binary	Social presence theory	X						
141	Ha and Geum (2021)	Technological Forecasting and Social Change	Binary	Quality function deployment	X						Service
142	Radicic and Petković (2023)	Technological Forecasting and Social Change	Binary	Resource-based view	X				Disruptive		Product and Process
143	Boccali et al. (2022)	Technological Forecasting and Social Change	Binary	Fractional programming	X						
144	Dwivedi et al. (2022)	Technological Forecasting and Social Change	Binary	Gray theory	X		X				Process
145	Nam et al. (2023)	Technological Forecasting and Social Change	Binary		X						
146	Brewis et al. (2023)	Technological Forecasting and Social Change	5Vs	Dynamic capability		X		Radical	Disruptive		Process
147	Saura et al. (2023)	Journal of Technology Transfer	Binary		X						Business model
148	Shin et al. (2023)	Technological Forecasting and Social Change	Binary	Quadruple Helix	X						

(Continues)

TABLE 1 | (Continued)

Paper details			Big-data conceptualization		Big-data outcomes			Contingency factors			
ID	**Authors and year**	**Journal**	**Dimensions**	**Theory used**	**Only benefits**	**Benefits & costs**	**Environmental & social sustainability**	**Radical & incremental**	**Disruptive & sustaining**	**Architectural, modular & component**	**Type of innovative outcome**
149	Justy et al. (2023)	Technovation	3Vs	Resource-based view and Dynamic capabilities		X			Disruptive		Process
150	Temiz et al. (2022)	Technovation	Binary			X					Service
151	Tahi et al. (2021)	Technovation	Binary	Network theory	X						Service
152	Cuomo et al. (2023)	Technological Forecasting and Social Change	5Vs		X						Process
153	Yu (2022)	Technological Forecasting and Social Change	Binary		X						
154	Seddigh et al. (2023)	Technological Forecasting and Social Change	3Vs		X		X				Service
155	Visconti-Caparrós and Campos-Blázquez (2022)	Technological Forecasting and Social Change	Binary	Modularity theory	X						
156	Patrucco et al. (2023)	Technovation	7Vs	Absorptive capacity	X						Service
157	Han and Trimi (2022)	Technological Forecasting and Social Change	Binary		X	X					Process
158	Xu et al. (2023)	Technological Forecasting and Social Change	3Vs		X		X				Process
159	Gokhberg et al. (2023)	Journal of Technology Transfer	Binary		X		X		Disruptive		Service
160	Cho et al. (2023)	Technovation	Binary		X						Product

et al. 2023; Patrucco et al. 2023). The above-mentioned results highlight the scattered landscape in terms of conceptualizing big data, with different frameworks at varying levels of multidimensionality. Another aspect that emerged, though only mentioned marginally in a few papers, is the way big data is owned and managed. In this respect, the first consideration leads to the distinction between private data and open data (Temiz et al. 2022). Big data generated and owned by private organizations for better innovation falls under the former category. Open data is when big data is available to anyone or selected partners who are interested in freely using it. Innovations may indeed be favored by both kinds of big data, bringing benefits to firms. The second consideration involves the concept of thick data (Mortati et al. 2023). Indeed, it has been argued that when data is rooted in quantitative analyses, it is considered big data, and when it is in the form of qualitative observations, it can be termed thick data.

As concerns the theories used, the studies we examined adopted different lenses to analyze big data in the context of innovation. Specifically, 19 studies adopted the resource-based view for their theoretical grounding (e.g., Akter et al. 2020; Shan et al. 2020; AlNuaimi et al. 2021; Ashaari et al. 2021; Cappa et al. 2021; de Souza et al. 2021; Kristoffersen et al. 2021; Mariani and Nambisan 2021; Choi and Park 2022; Fukawa and Rindfleisch 2023). From this perspective, big data is recognized as a valuable resource that can be used by companies under the proper conditions. Another considerable set of manuscripts, namely 11, adopted the theory of dynamic capabilities (e.g., Johnson et al. 2017; Dubey et al. 2019; Rialti et al. 2019; Arora et al. 2020; Shamim et al. 2020; Fukawa and Rindfleisch 2023; Pedota 2023). Another group of studies focused on stakeholder theory to grasp the overall effects of big data used for innovation (e.g., Gupta et al. 2019; Jabbour et al. 2019; Kamble et al. 2021; Modgil et al. 2021; Bag et al. 2023). In fact, big data has implications not only for the firm but for all the parties involved as well, e.g., customers and suppliers. Human capital theory was adopted by three papers (Naccarato et al. 2018; Mahmood and Mubarik 2020). In these instances, big data is recognized as a valuable source if companies include people with the right capabilities and knowledge to interpret and analyze large amounts of information with the aim of later extracting valuable insights. In addition, to examine the outcomes of big data, which can be uncertain, some have applied fuzzy set theory (e.g., Yadegaridehkordi et al. 2018; Kazancoglu et al. 2021; Kim and Geum 2021; Llopis-Albert et al. 2021; Yakubu and Kwong 2021; Xuan 2022). Moreover, four studies used the institutional-based view to analyze big data, thus considering the different formal and informal differences that can arise when collecting and utilizing data (e.g., Bag et al. 2021; Irwin et al. 2021; Di Vaio et al. 2022). Two studies made use of agency theory to understand how big data influences innovation by leveraging various corporate governance mechanisms (Manita et al. 2020; Ibrahim et al. 2021). Furthermore, certain studies have considered the centrality of big data collected by various entities involved in innovation activities and consequently employed open innovation (Akhtar et al. 2019; Boeing and Wang 2021; Gupta et al. 2021) and user innovation perspectives (Liu et al. 2018; von Hippel and Cann 2021). Connected to this approach is the stream of research that avails itself of social network theory to study big data, which is seen as the result of relationships between the many parts involved (e.g., Dotsika and Watkins 2017; Chang 2018; Jun et al. 2018; Hofmann et al. 2019; Zhang, Yan, and Guan 2019; Tahi et al. 2021). Certain other manuscripts used value creation and value capture frameworks (Sorescu 2017; Urbinati et al. 2018) to distinguish the ways in which organizations can collect valuable big data from the ways they use the big data collected internally or bought from external entities in order to extract value. In addition, organizational information processing theory has also been put to use by three studies (Roßmann et al. 2018; Benzidia et al. 2021; Yu, Zhao, et al. 2021). On top of the numerous theoretical approaches mentioned so far, yet other manuscripts considered big data itself to be an emerging theory (Akhtar et al. 2019; Liu et al. 2019; Sheng et al. 2019). In addition to this, many other theories were applied a single time in the studies considered, as reported in Table 1.

4.2.2 | Big-Data Outcomes

As concerns the type of effects generated by big data, the majority of the studies reported a positive impact for organizations. More specifically, 132 publications focused on the benefits of big data, overlooking any possible negative aspects (e.g., Urbinati et al. 2018; Akhtar et al. 2019; Sestino et al. 2020; Kamble et al. 2021; von Hippel and Cann 2021; Plantec et al. 2023). In contrast, 29 documents explicitly considered the drawbacks of big data as well (e.g., Jabbour et al. 2019; Bag et al. 2021; Chang 2021; Chaudhary et al. 2021; Meadows et al. 2021). Among these papers, the main issues relating to big data that need to be considered by organizations were identified as the following: those related to privacy concerns for individuals, those connected to security issues for sensitive information regarding organizations, and those linked to costs for data management and analysis.

We also analyzed whether, regarding big data and innovation, these studies considered environmental and social implications rather than just economic aspects of sustainability. In 3877 instances the manuscripts also referred to positive possible effects in environmental and social sustainability (e.g., Chandy et al. 2017; Dubey et al. 2019; Kamble et al. 2021; Kazancoglu et al. 2021; Modgil et al. 2021; Bag et al. 2023). For example, it has been argued that big data "*enables the integration of sustainability considerations*" (Xu et al. 2023, 6) and that digital (e.g., big data) and social needs are strongly interconnected (Gokhberg et al. 2023). Indeed, companies are increasingly implementing innovative CSR initiatives that consider big data (Choi and Park 2022). More generally, it has been argued that innovations involving big data help to solve grand challenges (e.g., Chandy et al. 2017; Gao et al. 2023).

4.2.3 | Contingency Factors

Different types of contingencies have emerged concerning the characterization of innovations. Moreover, just a minority of studies differentiated between the various types. In particular, 11 papers mentioned the radical type of innovation (e.g., Gupta et al. 2019; Mahmood and Mubarik 2020; Kiani Mavi and Kiani Mavi 2021; Brewis et al. 2023). Within this group of papers, only a few also referred to the sustaining type of innovation (Johnson et al. 2017; Rialti et al. 2019; Mahmood and Mubarik 2020; Kiani Mavi and Kiani Mavi 2021). Among these 11 papers, the majority also recognized the multidimensionality of big data. Many papers dealt with the concept of disruptive innovations and sustaining innovations, i.e., 27. However, only one study also referred to sustaining innovations (Urbinati et al. 2018), while most studies focused mainly on disruptive innovations (e.g., van den Broek and van Veenstra 2018; Fernández-Rovira et al. 2021; Han et al. 2021; Mariani and Nambisan 2021; Modgil et al. 2021; Plantec et al. 2023). In this case, the majority of the studies relied instead on dichotomous interpretations of big data rather than a multidimensional one. Furthermore, only one study mentioned the architectural innovation concept (Chalvatzis et al. 2019), and none considered the modular and component types of innovation. Moreover, 83 manuscripts explicitly dealt with the "process" type of innovation (e.g., Kwon et al. 2018; Roßmann et al. 2018; Jabbour et al. 2019; Julsrud and Krogstad 2020; Liu et al. 2021), while 41 discussed "product or service" innovations (e.g., Johnson et al. 2017; El-Kassar and Singh 2019; Shen et al. 2019; Zhang, Du, et al. 2019), and 12 focused on "business model" innovations (e.g., Urbinati et al. 2018; Nguyen Dang Tuan et al. 2019; Sestino et al. 2020; Llopis-Albert et al. 2021).

5 | Discussion and Future Research Directions

The SLR we have conducted on publications published in top management journals can benefit a wide audience of scholars, managers, and policymakers, as it sheds light on our current understanding of the impact that big data has on innovation and of what else still needs to be explored. In the following subsections, we discuss our findings and highlight promising future research directions for each of the three areas of interest identified in this study, as also summarized in Figure 3.

5.1 | Big-Data Conceptualization: Which Is the Right Path?

Compared to the initial consideration of big data as a binary concept, i.e., being present or not, research is moving toward recognition of the different dimensions of big data. There are still studies that consider big data as a dichotomous concept, disregarding the differences that may arise within the label of big data, but is this correct? It is increasingly being acknowledged that high volume is not enough to be properly considered big data, "*no matter how big*" (Chandy et al. 2017). In order to properly understand the benefits as well as the costs of big data, it has been argued that it is useful to recognize the existence of "*other dimensions*" besides just volume (Cappa et al. 2021). The majority of the studies where multidimensionality is conceptualized have converged on the 3V framework, which adds "velocity" and "variety" to the volume dimension. Velocity addresses the fact that data must be updated and collected in a fast manner or even in "*real time*" (Chang 2021), while variety underscores the importance of "*different types of data*" (Weerasinghe et al. 2022) in a dataset. Having a lower quantity of data with much information per observation and collected in almost real time may thus constitute more comprehensive big data than just a simple huge dataset with little information and old data. Understanding of this aspect may still not be fully clear, and it thus deserves further attention.

In addition, another widespread framework in the literature is the 5Vs, where the "veracity" and "value" dimensions are added. Veracity is connected to the need for "*human resources to prepare for the analysis of large data-related issues*" (Nguyen Dang Tuan et al. 2019, 13). Indeed, the need for "*analytical personnel*" to deal with big data (Wang et al. 2018, 9) is also noticeable in the numerous positions and job postings for this role worldwide. Value, on the other hand, concerns the fact that data should be "*meaningful*" (Čábelková et al. 2021) for the company and that the "*presence of internal practices and methods*" is required (AlNuaimi et al. 2021). Leveraging the 3Vs or 5Vs, which are the most common categorizations of big data used in previous studies, or even the most recent and expanded 6Vs or 7Vs, will indeed favor scholarly reasoning on each dimension in terms of pros and cons. The identification of big data as multidimensional bolsters a more careful consideration of the phenomenon rather than simply seeing it as dichotomous. It is worth noting, in connection with the following subsection, that almost two-thirds of the articles that considered the drawbacks of big data also considered big data to be not a dichotomous variable but rather one composed of various dimensions, which further highlights the relevance of multidimensionality. Thus, to more comprehensively grasp the effects produced by big data, future research in the innovation field needs to shift toward consideration of a multidimensional perspective. Moreover, there is a need for alignment in terms of a shared framework in order to better understand how it may be possible to leverage big data for innovation. The challenge is to find a balance between the complexity created by the inclusion of an increasing quantity of V dimensions, on the one hand, and the need, on the other hand, for simplicity, in a comprehensive and applicable conceptualization of big data for innovation. A convergence toward a common framework might be helpful for scholars, managers, and policymakers to achieve a greater and shared understanding of big data for innovation. It could be extremely useful to understand which framework could be the best tradeoff between a detailed and focused conceptualization of big data for innovation and its complexity.

Consequently, interesting future research directions regarding this aspect, which we have also summarized in Figure 3, might be: Can we consider big data a dichotomous concept? What are the advantages of adopting a multidimensional framework for big data and innovation? Which of the big data frameworks proposed is considered the most by firms when innovating? How many dimensions are needed to properly grasp the effects of big data for innovation? Does consideration of the multidimensionality of big data allow us to more clearly identify the benefits and drawbacks connected with big data and innovation? What are the advantages of innovating activities when the different dimensions constituting big data are identified? What benefits and drawbacks for innovating activities are linked to each of the big data dimensions identified?

In addition, the distinction between private data and open data should be explored further. Indeed, this aspect may involve

FIGURE 3 | Future research directions for big data and innovation, divided into the areas identified in this study.

differences in studying and managing big data and innovation. Adopting an open data approach, i.e., sharing data, does not imply a loss of the benefits that come from big data for innovation, but rather a change of paradigm. Allowing other entities to use the data collected may lead to new, unexpected innovations emerging, in collaboration with another firm or independently. Moreover, such innovation may ultimately benefit the market served by the firm. Of course, this necessitates different ways of organizing collaborations with stakeholders, including legal aspects. Thus, scholars, managers, and policymakers should more attentively consider the possibility of adopting the open data framework, as well as a definition of the ways in which companies can implement such a process. Furthermore, the difference between big data and thick data, i.e., entirely numerical or qualitative data, has also been highlighted. This is another aspect that has barely been addressed so far in previous research but that deserves far more attention. Indeed, when dealing with big data, we should make a distinction depending on whether quantitative information can be complemented with contextual qualitative data. Recognizing the differences between the two types of data (i.e., quantitative and qualitative) and jointly leveraging them might be extremely valuable for organizations. Therefore, a potential research question is the following: How can firms adopt an open data approach and benefit from big data? What are the benefits and drawbacks associated with open data? Which stakeholders are the most suitable to include in an open data initiative? How can firms adopt either a thick data or big data approach, depending on the circumstances? What are the benefits and drawbacks of thick data over big data? How can firms effectively collect, manage, and use thick data?

The theoretical approach used may also contribute to a better understanding of big data for innovation. There have been various lenses applied in previous studies. Those most commonly used to analyze the impact that big data has on innovation have been the resource-based view and dynamic capability theory. It is interesting to note that among the papers that used these two theoretical lenses, the majority recognized big data as multidimensional. This is very impressive considering that, in contrast, the majority of the studies overall relied instead on a binary conceptualization. Therefore, these theories might be the right ones when considering the multidimensionality of big data in an innovation context. Other widely used forms of theoretical grounding were stakeholder theory, fuzzy theory, social capital theory, and human capital theory. When the research also contemplated the costs and risks associated with big data, the theories used were the resource-based view, the dynamic capability approach, stakeholder theory, and institutional and agency theories. This suggests that these theoretical approaches allow researchers to better consider the overall effects of big data and innovation. In addition, big data has also been considered to be a theory itself, which exemplifies the fact that this phenomenon is far from clear. It is worth noting that the few studies that considered big data as a theory were not the most recent (i.e., 2019), which shows that scholars are converging toward the adoption of a variety of established theories to achieve a deeper understanding of big data and innovation. In fact, the literature explicitly reports that "*there is a lack of theories and conceptual maps to instruct researchers around big data themes*" (Sheng et al. 2019, 6) and that the "*theoretical perspective … could be also enriched*" (Urbinati et al. 2018, 12) through "*different theoretical frameworks*" (Gupta et al. 2019, 7). An explicit suggestion, for example, refers to "*social network analysis*" (Chang 2018). As big data can be a resource collected from external sources, through which companies may collaborate in the creation of new knowledge, some studies have also considered big data in relation to the open innovation framework. In particular, it has been argued that an "*open innovation framework can be used to further capture value from big data*" (Cappa et al. 2021, 15). We contend that future studies should continue to examine it from different theoretical angles in order to fully probe the phenomenon of big data for innovation, further scrutinizing the theories that have already been used and also implementing other new forms of theoretical grounding. In this way it may be possible to properly understand the antecedents, management, and effects of big data and innovation. Future research could consider, in addition to the approaches that have already been utilized or suggested by previous studies, as reported above, even more theoretical perspectives that could be suitable in this context, such as signaling theory and real option theories. In fact, big-data collection and usage may signal an organization's efforts to achieve digitalization, which can affect performance as well as relationships with stakeholders, making this emerging framework applicable. In addition, if researchers used a real options approach, it would be possible to see big data adoption as happening step by step, i.e., first collecting or acquiring big data and only in certain cases using it later on. Therefore, given the complexity of the phenomenon, the focus might be on theory deepening, i.e., leveraging already applied theoretical lenses, on theory transplantation, i.e., dragging theories from other contexts, and on theory combination, which bridges the different lenses adopted so far. Such a plurality of theories could allow us to open the black box of big data and innovation and lead to a more detailed understanding of the effects it may have for firms. Examples of future research questions regarding the theoretical approach that could be explored include: Which theory allows us to comprehensively consider all aspects related to big data and innovation? How can big data for innovation be analyzed using real options theory? How can big data for innovation be analyzed using signaling theory?

5.2 | Big-Data Outcomes: How to Properly Dissect Them?

Concerning outcomes, the majority of studies considered only the benefits arising from big data and innovation. Interestingly, the great majority of these papers also considered big data as a dichotomous concept, suggesting a parallel between not considering multiple dimensions of big data and not acknowledging the drawbacks associated with it in the innovation domain.

Only a small portion of papers considered the negative aspects of big data, whereas many of these aspects need to be considered when handling big data for innovation, including "*potential issues related to data security and privacy*" in cases of data breach (Sestino et al. 2020, 7). These risks may be compensated by insurance, which constitutes an additional cost for companies (Cappa et al. 2021). Moreover, it has emerged that costs for data management and analysis also need to be considered when discussing big data (Cappa et al. 2021). Due to the nature of big data, the storage space and staff needed to analyze the information collected must also be borne in mind. In fact, our SLR further highlights the existence of a dark side to big data. However, the negative aspects of big data should be more carefully scrutinized by researchers in the innovation field, as well as by managers, because currently they are too focused on the innovative benefits that may spring from big data. Future research should devote greater thought to the identification of the drawbacks of big data as well as to properly identifying ways to mitigate and "*overcome them*" (Urbinati et al. 2018). In addition, the benefits should also be further scrutinized, especially in terms of sustainable development. Given a growing focus on grand challenges, i.e., the pressing social and environmental issues of today, organizations are increasingly attempting to deliver benefits not only in economic terms, but also for the environment and society. In this regard, only a few of the studies considered in this literature review, as reported above, have focused on environmental and social aspects when dealing with big data and innovation. The studies that also considered the impact on environmental and social sustainability aspects relied on a multidimensional view of big data. Above all, multidimensionality leads to a deeper understanding of both the benefits and drawbacks, in economic terms, and also of the environmental and social aspects. Future studies could make a greater effort to understand the combined effect of economic, environmental, and social aspects "*to ensure all stakeholders can benefit from … big data*" (Chang 2021, 10). Similar to the definition of "open sustainable innovation" (Collevecchio et al. 2024), which leverages open innovation blended with sustainability aspects, it might be interesting to develop a framework (and possibly coin similar terminology) for the case of firms handling big data for social and environmental sustainability objectives. In addition, a more comprehensive examination of performance metrics is also suggested, leveraging a focus on "*long-term implications*" (Troilo et al. 2017) and the possibility of nonlinear effects like "*'U' and 'S' shaped relationships*" (Xie et al. 2021). Moreover, it is still not entirely clear how to manage big data so that the benefits outweigh the drawbacks. This is also due to the fact that big data for innovation has so far been considered a black box, whereas greater understanding of the processes involved is needed.

Based on the above, possible future research questions regarding big data outcomes include: What are the drawbacks linked to big data and innovation? How can big data foster innovation while maintaining data privacy and security? What are the most dangerous perils for innovations linked to big data? How can firms handle the drawbacks of big data for innovation? How can the costs and risks associated with big data in innovation be mitigated by companies? What are all the benefits linked to big data and innovation in social and environmental terms? How can big data nurture innovations that achieve social and environmental benefits? Does big data for innovation help companies improve their sustainability performance? When does big data affect firm innovation positively/negatively/in a curvilinear manner? When do the benefits of big data outweigh the costs? Which V dimension is associated with which benefit and drawback? Which V dimension is crucial to achieving environmental and social sustainability aims? How can firms leverage big data for innovation to ensure the benefits outweigh the costs? Which processes may firms implement to enhance performance when leveraging big data for innovation?

5.3 | Contingency Factors: When Is It Possible to Unlock the Value of Big Data and Innovation?

Big data has different characteristics and implications depending on the innovation context in which the firm operates. Therefore, contexts may change the way big data for innovation is considered and handled and which outcomes are produced. A critical contingency factor in properly studying big data and innovation is the type of innovation considered. Indeed, it has also been stated recently that "*big data ... could be further analyzed by considering ... types of innovation*" (Cappa et al. 2021,14). Concerning the types of innovation linked to big data, a few studies have gone in this direction by distinguishing between radical and incremental types and disruptive and sustaining ones. However, as only a few studies go in this direction, further efforts should be dedicated to it, as big data may be used in a different way depending on the type of innovation considered or targeted by companies. For example, large amounts of information on customers might be more useful for incremental and sustaining innovation, whereas big data coming from non-customers might be more suitable for radical and disruptive innovation. Indeed, the information deriving from organizations or individuals with whom a firm has a non-familiar relationship, e.g., non-customers or companies with whom they have never interacted before, could yield different types of input insights and spur innovation. Future research should also devote greater attention to the concept of ambidexterity, which was also recently highlighted (Rialti et al. 2019; Meadows et al. 2021). Moreover, it is also a fact that a majority of the studies that focused on the radical type of innovation adopted a multidimensional framework for big data. On the other hand, when disruptive innovation is considered, the opposite happened, i.e., the majority of these studies applied a binary interpretation of big data. This difference deserves further study in order to better align the conceptualization and outcomes of big data and innovation. We contend that neither big data nor innovation should be considered to be simple binary concepts, but rather it should be clear that there is a great deal of unlocked and not fully comprehended value in considering the various dimensions, which, in the case of innovation, means distinguishing between its various types. Moreover, other categorizations of innovations, like "*architectural versus modular*" (Cappa et al. 2021), have been nearly absent in the literature so far. However, we contend that they are worth examining when studying big data in order to better understand the role big data plays in each of the different types of innovation. Concerning the types of outcomes achieved thanks to the use of big data, the majority of the studies focused on the process type of innovations, which highlights their relevance in this context. Although less attention has been devoted to the difference between product, service and business model innovations, there are additional opportunities to be explored in these contexts, too. Interest should also be directed to which V dimension may be more crucial for one type of innovation or another.

Based on the above, examples of future research questions regarding big data and types of innovation could include the following: What effect does big data have on radical and incremental innovation? How can big data be handled for radical or incremental innovation? What effect does big data have on disruptive and sustaining innovation? How can big data be handled for disruptive or sustaining innovation? What effect does big data have on component and architectural innovation? How can big data be handled for component or architectural innovation? Which dimension of big data is more important for radical/incremental innovation? Which dimension of big data is more important for disruptive/sustaining innovation? Which dimension of big data is more important for architectural/modular innovation? What effect does big data have on product and process innovations? How can big data be handled for product and process innovations? How can organizations leverage big data depending on the type of innovation they want to accomplish? What kind of innovation is favored by a specific V dimension of big data?

6 | Conclusions

The total amount of global data is expanding massively, and companies are seeking to better understand how big data can be collected, managed, and interpreted. For these reasons, there is increasing scholarly, managerial, and policymaking ferment around big data and the benefits that can arise. In this study, we have responded to the call for further studies regarding the impact big data has on innovation for organizations (Coussement et al. 2017; Cappa et al. 2021). In particular, the SLR we conducted expands scientific and managerial understanding of the big data phenomenon in the innovation domain, and it delineates promising future research directions. Thanks to the approach adopted in this study, we have been able to provide numerous contributions.

Firstly, we have inductively identified three main aspects, also summarized in the framework reported in Figure 2, which should be considered in the context of big data and innovation: (i) big-data conceptualization; (ii) big data outcomes; and (iii) contingency factors. In this way, we have provided advice for scholars, managers, and policymakers regarding which aspects to consider in order to properly explore this emerging phenomenon. Secondly, we have summarized the current state of the literature regarding the three main aspects that we highlighted. We have thus identified what was done in each of the directions that we argued were critical. It has also emerged that these three aspects are related to each other in the research conducted so far. This overview gives scholars, managers, and policymakers a quick and updated indication of what has been researched so far and by whom, organized around the three dimensions identified, with the aim of facilitating opportunities to properly leverage big data for innovation. Thirdly, we recognize that this body of literature has so far overlooked certain relevant issues. Thus, this SLR also sought to contribute to potential future developments in big data and innovation by detailing promising research directions, as also summarized in Figure 3, which might be useful for a wide audience. In this SLR, we used both the gap-spotting and the problematizing approach, which were both found to be critical in producing interesting and useful research outcomes in management research and in nurturing future developments (Alvesson and Sandberg 2013). On the whole, the insights provided by this study may aid scholars, managers, research centers, and policymakers when managing big data and innovation to advance products and services, enhance technology transfer, and improve performance.

This study is not exempt from limitations, but these indicate ideas for further studies in the future. Firstly, whereas we conducted our literature review by considering only 4*, 4, and 3 level journals dealing with innovation, as per their ABS rankings, future studies could also consider 2 and 1 ABS ranked journals and other ABS categories, such as information systems, to provide a broader look at scholarly work on this topic. Furthermore, future studies should consider additional years for their SLRs to further map how the phenomenon is evolving. In addition, other rankings or strategies for the inclusion of papers could be considered to identify a different sample for a literature review. Moreover, future studies could conduct similarly focused literature reviews on other organizational functions to further enrich our understanding of big data.

Author Contributions

Francesco Cappa: conceptualization, methodology, validation, formal analysis, data curation, writing – original draft, writing – review and editing, visualization. **Chiara Acciarini:** conceptualization, methodology, validation. **Raffaele Oriani:** conceptualization, validation. **Paolo Boccardelli:** conceptualization, validation.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Endnotes

[1] The authors administered a survey to attendees of full-time and part-time MBA courses in 2020–2021 at a leading European business school.

[2] The results were the same with the most recent 2024 ABS list, which was released during the review process of this paper, as there have not been changes in the 3, 4, and 4* ranked journals for the "innovation" category.

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