International Journal of Information Management 56 (2021) 102231

Contents lists available at ScienceDirect

International Journal of Information Management

journal homepage: www.elsevier.com/locate/ijinfomgt

Big Data Analytics in Building the Competitive Intelligence of Organizations

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ARTICLE INFO

Keywords:
Big Data analytics
Competitive intelligence
Analytical capabilities
Competitive advantage

ABSTRACT

Over recent years, organizations have started to capitalize on the significant use of Big Data and emerging technologies to analyze, and gain valuable insights linked to, decision-making processes. The process of Competitive Intelligence (CI) includes monitoring competitors with a view to delivering both actionable and meaningful intelligence to organizations. In this regard, the capacity to leverage and unleash the potential of big data tools and techniques is one of various significant components of successfully steering CI and ultimately infusing such valuable knowledge into CI strategies. In this paper, the authors aim to examine Big Data applications in CI processes within organizations by exploring how organizations deal with Big Data analytics, and this study provides a context for developing Big Data frameworks and process models for CI in organizations. Overall, research findings have indicated a preference for a rather centralized informal process as opposed to a clear formal structure for CI; the use of basic tools for queries, as opposed to reliance on dedicated methods such as advanced machine learning; and the existence of multiple challenges that companies currently face regarding the use of big data analytics in building organizational CI.

1. Introduction

Twenty years ago, Powell and Bradford (2000: 181) stated that "*current management approaches to resource-based strategy and core competence thinking require extensive gathering to ensure that correct assumptions are being made about the environment and competitors' capabilities. Without such intelligence any attempts to develop, maintain and in many cases even identify the key assets and competences are flawed*."

The years since then have seen an exponential increase in the volume, variety, velocity, and value of large amounts of data (Larson & Chang, 2016; Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015), which has led to the emergence of Big Data processing trends, in particular, fast analytics and data science becoming part of business intelligence (Larson & Chang, 2016), or Big Data analytics implementation within organizations dealing with ubiquitous digital data. On the one hand, organizations are administered by information technology, knowledge, intelligence and wisdom (Davenport & Harris, 2007; Liautaud & Hammond, 2002; Wixom & Watson, 2010) while, on the other hand, Big Data (McKinsey Global Institute, 2011) goes beyond the use of the usual databases and software tools to capture, store, manage and analyze, as it involves a broad range of massive and new data types to uncover new opportunities in organizations (Davenport, 2014). Therefore, nowadays, more and more firms around the world are competing to understand big data in deeper and clearer ways (Morabito, 2015; Rehman, Chang, Battol, & Wah, 2016), in which Big Data analytics and business intelligence are considered important information processing mechanisms for organizations and can help to reduce uncertainty and equivocality in different types of decision-making processes (Kowalczyk & Buxmann, 2014).

Value creation for companies has become a major sustainability factor, in addition to profit maximization and revenue generation, and, nowadays, modern companies collect Big Data from various inbound and outbound data sources with this in mind (Rehman et al., 2016). Initially, the adoption of Internet of Things (IoT), Big Data, and cloud computing technologies has led to better value creation for both the customer and the enterprise and, more recently, Competitive Intelligence (CI) has attracted abundant attention because of the explosion of data now publicly available through mobiles phones, social media, blogs, wikis, text messages, e-mails, and other electronic digital communications; such data from these domains serves as an important instrument for building CI. Most of organizations have adopted Social Mobile Analytics Cloud (SMAC)-based data strategies. In the present

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https://doi.org/10.1016/j.ijinfomgt.2020.102231
Received 4 February 2020; Received in revised form 18 August 2020; Accepted 18 August 2020
Available online 28 September 2020

world, Big Data is one of the primary sources of CI (Chen, Chiang, & Roger, 2012; Larson & Chang, 2016; Hartmann, Zaki, Feldmann, & Neely, 2016), in which Competitive Intelligence (CI) consists of the entire process of transforming unorganized competitor data into strategic knowledge (Tyson, 1998). Adopting Big Data methods for better CI impact enables information gathering from a large, diverse pool of data towards meaningful insights, trends, patterns, and knowledge for predicting, forecasting, analyzing, describing, prescribing and diagnosing competitor scenarios. As indicated in a systematic literature review on Big Data with cognitive computing, Gupta, Kar, Baabdullah, and Al-Khowaiter (2018: 78) have stated that "*Big Data analytics has gained significant amount of importance as it enables organizations to be ahead of their competitors.*" These insights are extremely important for CI in achieving better positioning and branding of firms.

To date, research studies on the interface between Big Data analytics and cognitive computing have yet to focus on its implications for decision making (Goes, 2014; Gupta et al., 2018), and academic research on the effects of Big Data development on firms' performance is still in its infancy (Raguseo, 2018). In this regard, Camargo Fiorini, Pais Seles, Chiappetta Jabbour, Mariano, and de Sousa Jabbour, 2018: 112) have stated that "*the body of research into Big Data so far lacks an academic work capable of systematizing the organizational theories supporting Big Data domain.*" Accordingly, this paper investigates the extent to which big data models and methods are practiced in CI processes in organizations. A framework is suggested based on gaps identified from the literature review. Taking a lead from the gaps identified and the framework defined thereby, the study attempts to find answers to the following questions:

1 *How do organizations build intelligence in CI cycles?*
2 *Which Big Data methods are practiced in CI processes?*

Building on the research findings, a theoretical argument on the importance of Big Data methods in CI cycles for greater impact is constructed and then a process model is built. A conjectural approach explaining CI requirements and analytical capabilities for organizations is then proposed. The discussion section interprets the further relevance of Big Data in CI operations based on the findings, and the paper concludes with the managerial implications, future research directions and the limitations of the study.

2. Literature review

According to Frizzo-Barker, Chow-White, Mozafari, and Ha (2016: 412), who provided a valuable systematic literature review on Big Data across business scholarship between 2009 and 2014, "*although the field is in its earliest stages of scholarly development, we found clear evidence of the energy and increasing interest focused on Big Data studies in business.*" Numerous studies have examined Big Data initiatives in organizations. These include the Big Data revolution in corporate strategies and management (George, Haas, & Pentland, 2014); the impact of IT in organizational productivity (Chang & Gurbaxani, 2012); Big Data life cycle research works (Khan, Liu, Shakil, & Alam, 2017); machine learning frameworks on Big Data (Zhou, Pan, Wang, & Vasilakos, 2017); the evolution of big data (Lee, 2017); three tier-based big data strategy for organizations (Matthew & Mazzei, 2017); big data usage in media and entertainment (Carr, 2013); assessment of skills and needs of Big Data projects (Tambe, 2014); big data innovation (Brynjolfsson & McAfee, 2011); the importance of Big Data (Harris, 2013); the adoption of big data analytics by e-commerce startups (Behl, Dutta, Lessmann, Dwivedi & Kar, 2019; Dwivedi et al., 2019); Big Data predictive analytics and manufacturing performance (Dubey, Gunasekaran, Childe, Blome, & Papadopoulos, 2019; Wamba et al., 2017; Mikalef, Boura, Lekakos, and Krogstie (2019)); Big Data analytics and artificial intelligence pathway to operational performance (Dubey et al., 2020); superior organizational performance through Big Data predictive analytics (Gupta, Drave, Dwivedi, Baabdullah, & Ismagilova, 2019); Big Data analytics and supply chain ambidexterity (Wamba, Dubey, Gunasekaran, & Akter, 2020); factors influencing Big Data projects in organizations (Agarwal, 2015); Big Data management and value (Borkar, Mayuram, Sangudi, & Carey, 2016; Dwivedi et al., 2019; George et al., 2014; Wu et al., 2015; Koutroumpis & Leiponen, 2013); Big Data in decision-making processes and impactful parameters influencing Big Data decisions in organizations (Shamin, Zeng, Shariq, & Khan, 2019; Simkin, 2018); the use of Big Data in information systems research (Müller, Junglas, Brocke, & Debortoli, 2016; Surbakti, Wang, Indulska, & Sadiq, 2020; utilizing Big Data analytics for information systems research: challenges, promises and guidelines; as well as new opportunities for academia to prove the essence and effect of Big Data on business performance (Batistic & van der Laken, 2019).

Originally, organizations in general have used analytical techniques with statistics and advanced database methods such as data mining (Xu, Liao, Li, & Song, 2011), and earlier CI processes required extensive trial-and-error mechanisms using intuition-based qualitative and quantitative data for modelling. Gownder (2011) has observed that customer loyalty is in rapid decline, and there are firms that sell data to organizations on what customers watch, tag, post, listen to, comment on, link, read, like, etc. (Marr, 2017). Big Data gives organizations the ability to see things they otherwise would not be able to see. From now on, due to the emergence of Big Data tools, organizations will utilize such larger, more diverse competitor data sets to identify impacts, insights, and incongruities. Olszak (2014) investigated how organizational CI needs information tools and proposed critical success factors. However, a conceptual framework for the CI cycle from a Big Data perspective has not yet adequately been addressed. Some prior studies (Matthew & Mazzei, 2017) focused on Big Data as a tool and a strategy, whereas other studies (Nasri & Zarai, 2013) presented critical success factors for CI. Nevertheless, the research question: *How are Big Data applications practiced in CI processes*? has not yet been addressed. This key aspect has not been explored in detail in the extant studies in the literature. Though the potential value generated by Big Data is real and significant (Jagadish et al., 2014), and big data has been recognized as a new form of capital (Satell, 2014), there is a need for studies providing a consolidated framework for organizational CI from a Big Data perspective.

Nowadays, organizations are interested in finding ways of engaging more with real-time insights dealing with competitors. Organizations and market research firms believe that Big Data will bring big change, big value, big return on investment, big competition, and big impact at large scale in all business domains, including manufacturing, logistics, health care, retail, banking, insurance, financial services, government, etc. (TCS, 2012). Though Big Data is poised to bring change (George et al., 2014) in products and services with respect to building CI, it has not yet completely evolved into a sustainable social and economic model. Nonetheless, Big Data is relatively new in social sciences, particularly in management and organizational research (George et al., 2014), hence it is prudent to study the impact of Big Data models on CI processes.

2.1. Competitive Intelligence (CI)

Competitive intelligence can, from an organizational perspective, be defined as the collection, analysis, interpretation, and dissemination of strategic information at the right time for use in the decision-making process (Acharya, Singh, Pereira, & Singh, 2018). Although its practical origins date back many decades, its intellectual origins can be attributed to Michael Porter, who, in 1980, used the technique of competitive intelligence to analyze industries and competitors (Fourie, 1999). In a recent bibliometric review dealing with the main research fields related to intelligence, Lopez-Robles, Otegi-Olaso, Porto Gomez, and Cobo (2019: 36) have found that Competitive Intelligence is the third most frequent thematic area within those mapped, and the authors state that CI "*is closely related to other thematic areas such as the* *management of information and knowledge, decision-making, and business strategy. […] Competitive Intelligence links the remaining Intelligence approaches and the organization's strategy to Business Intelligence. This makes Competitive Intelligence a core model in its own right within the field of strategic management, competitiveness, and the knowledge economy."*

Organizations use CI to gather and analyze information about competitors in order to gain an edge in the (Kamboj et al., 2018) marketplace (Du Toit, 2003; Blenkhorn & Fleisher, 2005; Amarouche, Benbrahim, & Kassou, 2015; Kamboj, Sarmah, Gupta, & Dwivedi, 2018; Sewdass & Du Toit, 2014). The Society of Competitive Intelligence Professionals (SCIP, 2015) defines CI as a systematic and ethical procedure towards gathering, analyzing, and managing external business information that impact and affect the company's plans, decision-making approaches, and operations. Kahaner (1998) has conceptualized it as a method for monitoring the competitive environment, with the goal of providing actionable intelligence in the organization (Chang & Lee, 1992; Walle, 1999; Sewdass & Du Toit, 2014). Ghannay and Mamlouk (2012) have defined CI as knowledge and foreknowledge about the external operating environment that ca improve decision making. The CI cycle is a methodology for acquiring, gathering, evaluating, and analyzing unformatted and raw business data and transforming them into finished intelligence for policymakers (Bose, 2008). The literature often describes CI practice as a five-step formal and informal process, ranging from planning, information gathering and analysis, and information dissemination to feedback of intelligence (Kahaner, 1998). There are cases (Herring, 1998) in which organizations have tried to use every available intelligent mechanism to collect, store and analyze competitor information, but have struggled to make the best use of the information. CI processes (Gilad & Gilad, 1985; Gilad, 1989; Porter, 1980) focus on those strategic intelligence issues of highest importance to senior management. CI provides information about the present and future behavior of competitors, and the general business environment (Vedder & Guynes, 2002). It is the first step towards guiding the planning and redesign of processes, products, and organization structures (Guimaraes, 2000). Companies using CI to analyze competitors' strengths and weaknesses are better able to predict market development opportunities and have superior performance to their competitors (Britt, 2006). Information about competitors is extracted from sources such as media (traditional and new), patent data, field visit records, sales force data, trade expositions, customer surveys, annual reports of competitors, interviews with third parties, all media reports, commissioned research, and industry trend reports (Subramanian & IsHak, 1998). CI is intrigued by the continuously evolving industry forces and competitor dynamics in the marketplace (Prescott & Gibbons, 1994).

The purpose of CI is to create useful knowledge towards internal business promotion and risk reduction through shared information resources (Priporas, Gastoris, & Zacharis, 2005). CI has been used by organizations for developing smarter and wiser strategies for competitive advantage (Vedder & Guynes, 2002; Wright & Calof, 2006). Interestingly, at a country level, Sewdass and Du Toit (2014) investigated the current state of competitive intelligence in South Africa and found that 60% of respondents strongly agreed that the most important CI activity in their organization was to use CI to remain cognizant of government legislative trends, which points to the need to improve stakeholders' awareness of the spectrum of roles that CI can play in value creation.

The importance of organizational Business Intelligence (BI) and CI lies in enhancing customer satisfaction and increasing profitability (Olszak, 2014). While organizational business intelligence chiefly concentrates on collecting and analyzing data such as customer data, supplier data, etc., CI focuses on competitor data. Makadok, Barney, and Jay (2001) have defined CI as "informating market intelligence." Other researchers have addressed CI as a knowledge process directed at finding competitors and analyzing blind spots in the activities of CI (Gilad, Gordon, & Sudit, 1993). There could be two firms that aggressively compete in the same market with the same products; may collaborate in research and development; have linkages in supplier–customer relationships; or even share a geographic technology; but, if the CI information in one of the companies is mostly unstructured in form, then it will be a hard task to build Big Data models such as digital content analysis, behavioral analysis, clickstream analysis, etc.

2.2. Big Data

From now on, businesses will exist in a data-driven economy and witness organizational practices that have overcome old strategic management theories, are redefining information value chains and restructuring to reassess competitive forces. The definition and scope of Big Data is rather diverse (Dutcher, 2014). In a nutshell, the concept of Big Data consists of the organizational use of massive amounts of data to support more accurate decision-making processes (Goes, 2014). It refers not only to the voluminous amounts of data that must be processed and stored, but also to the nature of the data (IBM, 2012; Lycett, 2013). Hardware environments and software tools capture large datasets within a tolerable elapsed time (Teradata, 2015); it is that data which is too big, too fast, and too hard to be handled by existing tools (Madden, 2012). Boyd and Crawford (2012) define Big Data as a cultural, technological, and scholarly phenomenon that rests on technology, analysis and an induced mythology of uncertainties. Moreover, Frizzo-Barker et al.'s (2016) systematic literature review on Big Data showed that "*Big Data remains a fragmented, early-stage domain of research in terms of theoretical grounding, methodological diversity and empirically oriented work*" (Frizzo-Barker et al., 2016: 403). More recently, Fiorini, Pais Seles, Chiappetta Jabbour, Barberio Mariano, and de Sousa Jabbour (2018) have suggested a research agenda on how to link organizational theories to Big Data research.

Originally, Big Data was characterized by the "3 Vs": *Variety, Volume, and Velocity* (Laney, 2001; Gartner., 2012; IBM, 2012). More recently, "7 Vs – *Variability, Veracity, Visualization, Value, Validity, Vulnerability, and Volatility* – have defined a Big Data ecosystem, with the relevant justification provided by DeVan (2016) and Firican (2017). Over the years, the volume, variety, velocity, and value of Big Data that organizations deal with has increased exponentially (Wamba et al., 2015). All of these Vs add relevance to the CI cycle. As the diversity of data sources is expanding (McKinsey Global Institute, 2011), it is prudent to use Big Data methods in order to achieve an organizational competitive advantage. When customers exchange views or ideas via online media, such interactions generate larger data (Archer-Brown, Piercy, & Joinson, 2013; Lazer, 2014). Current disruptive technology trends are seducing organizations to adopt Big Data, thereby moving organizations towards data apophenia.

The success of Big Data analysis and its accuracy depend heavily on the tools and techniques used to analyze the data (Bose, 2008). Gandomi and Haider (2015) have provided a consolidated description of Big Data by integrating definitions from practitioners and academics. There are some studies (e.g., Fulgoni, 2013; Lazer, 2014; Mishra, Singh, Rana, & Dwivedi, 2017; Tihanyi, Graffin, & George, 2015) that show that analyzing customers through Big Data models generates benefits in precision marketing, new product development, and realigning business strategy to maintain sustainable competitive advantage. Big Data methods such as text mining, web mining, social network analysis, mobile and multimedia mining constitute foundational technologies in organizational business intelligence and analysis (Chen et al., 2012). Boyd and Crawford (2012) have expressed doubts about the extent to which such large-scale massive Big Data methods have provided insights or not. Information dissemination, acquisition (Barua, Mani, & Mukherjee, 2012) and analysis, which can be used to further business strategy, are crucial to any organization. With a view to providing a valuable understanding of Big Data analytics, Gandomi and Haider (2015) have provided a brief overview of Big Data analytical techniques for both structured and unstructured data.

Organizations consider cost, flexibility, functionality, leadership, culture, and time as critical success factors for implementing Big

Intelligence (Ranjan, 2008). Studies on Big Data (Bendle & Wang, 2016; Erevelles, Fukawa, & Swayne, 2016; Hsinchun, Chiang, & Storey, 2012; Salehan & Kim, 2016; Vasarhelyi, Kogan, & Tuttle, 2015) have, on one hand, introduced structured data, which typically include online and offline ratings, questions with dichotomous answers, or questions with a limited or inadequate choice of responses whereas, on the other hand, unstructured data is amorphous, usually available in different data formats, and must be preprocessed to be usable for insights. Ren, Zhang, Liu, and Sakao (2019) and Bughin, Chui, and Manyika (2010) have set out Big Data-based start-up studies for businesses. Gupta et al. (2019) and Blazquez & Domenech (2018) have analyzed the economics of Big Data from a business point of view. Wang, Kung, and Byrd (2018) discussed Big Data methods and its benefits for healthcare organizations. Big Data has also been viewed as a strategic decision-making tool (Goth, 2015; Salehan & Kim, 2016; Duan, Edwards, & Dwivedi, 2019). Big Data podiums range from the typical common online transaction platforms used for transactional exchanges and operational exchange through to virtual platforms, such as social networking threads and clicks, open-design platforms, mobile interaction platforms, and anything that constitutes a digital platform (Faraj, von Krogh, Monteiro, & Lakhani, 2016). In recent years, the widespread use of digital platforms has enabled clusters of individual customers to congregate online and pursue desired products, services and/or shared interests, although these may be differentiated by time and space (Faraj et al., 2016). A small organization with a progressive attitude towards Big Data may be able to carve out a competitive advantage against a much bigger rival firm simply by understanding their niche in the data market better. As long as firms have access to rock-hard data – from both internal and external sources – the ingenious analysis of such data is what will produce competitive advantage. In this regard, for instance, Raguseo's (2018) empirical study on the benefits of Big Data technologies demonstrated that these have enabled better products and services to be provided as strategic benefits. As market competition is increasingly transforming into data-based races, a better perspective is needed on how Big Data models in CI cycles can bring competitive advantage.

3. Conceptual Framework

This section proposes a novel framework to illustrate how organizations can leverage Big Data analytics to enhance business value. There are standalone studies on the integration of BI and CI (Tuta, Zara, Orzan, & Purcarea, 2014); a theoretical presentation of a scenario-based method of CI analysis (Valeriu, 2014); social media (Facebook and Twitter)-based competitive analysis using text mining (He, Zha, & Li, 2013); critical success factors needed to achieve a successful implementation of KM and CI (Ghannay & Mamlouk, 2012); a conceptual framework for salespeople and CI (Rapp, Agnihotri, & Baker, 2011); graphical modelling to use Web 2.0 as a new source for mining CI (Kamal, 2015); the effectiveness of the CI spider tool in addressing some of the problems associated with using Internet search engines in the context of competitive intelligence (Chen, Chau, & Zeng, 2002); and the downstream impact of internet use on both CI and the organization (Teo & Choo, 2001). Ketter, Peters, Collins, and Gupta (2016)) have described data challenges in organizations based on a competitive benchmarking research method. It is evident that, although CI has largely captured the interest of researchers, there is a dearth of comprehensive and integrative Big Data method-based frameworks for CI processes in organizations.

To distinguish between rivals and partners, the strategic value of Big Data in CI plays a critical role. CI personnel are often faced with myriad questions: *What kind of data to collect? What are the methods to collect real time internal and external data? How can competitor data be transformed into meaningful patterns and knowledge? What types of insights can be predicted, interpreted, and analyzed for better CI*? Answers to these key questions will assist corporate strategists in deploying resources and deciphering how their firms' Big Data investments can translate into greater organizational CI success. Irrespective of the nature of the business, the organization's scope includes constantly updating its internal business strategies based on competitor movements. Understanding the nature of competitor data, both structured and unstructured, plays a critical role in analyzing CI cycles. Advanced Big Data methods enable organizations to receive alerts on real-time market fluctuations, competitors' moves, and customer mobility. The Big Data–CI application interface processes the data into meaningful insights. The framework presented below underlines the diversity of the external and internal data (see Fig. 1). Data preprocessing is essential before applying Big Data methods in CI cycles. Without proper data cleaning mechanisms, intelligence or smart insights cannot be built.

Collecting CI data without quality and security layers would induce organizational mistrust, create data ownership conflicts, increase costs, and lead to improper customer service, errors and outliers, time delays, etc. The CI data collection process should identify authoritative data sources and data entry points. Therefore, there is a need to benchmark CI processes using Big Data analytics. CI is always regarded as external source of information (Chen et al., 2002; Ross, McGowan, & Styger, 2012) and Big Data-enabled CI offers great business impact and benefits, such as creating new growth opportunities, being business ready in real time situations, enabling faster responses to changes in marketplaces due to competitor movements, and improving strategic plans by identifying potential vulnerabilities (Bose, 2008; Chen & Das, 2010; Ross et al., 2012). Owing to data sensitivity, privacy, and data-sharing challenges, it is always difficult for organizations to change their internal data strategies following comparison with external, competitor data. Many firms do not maintain CI databases for unstructured and social data. However, owing to the growing demands of Big Data, it is time organizations to recognize the need to invest in CI and use Big Data approaches to understand events in real time, identify any challenging triggers in competitors' strategies, and readjust internal promotions or policies accordingly.

4. Research methods

4.1. design and selection

The research approach adopted in this study is based on grounded theory (Eisenhardt, 1989; Strauss & Corbin, 1990). The clear purpose is to understand and offer a conceptual framework as well as define an empirical interpretation of a Big Data methodological approach in organizational CI cycles. Building on the gaps identified in the literature review, our study focuses on the following research questions:

1 *How do organizations build intelligence in CI cycles?*
2 *Which Big Data methods are practiced in CI processes?*

In order to reach our research objectives, an exploratory, theory-driven approach was selected (Pagell & Wu, 2009). This work explores how organizations collect and build intelligence, and how Big Data methods are practiced in CI cycles in organizations. According to Yin (2008), such an exploratory study is appropriate when addressing "*How?*" research questions regarding a contemporary phenomenon. Indeed, an exploratory study could help in exploring Big Data practices as the fields of both Big Data and CI are complex and we need contextual phenomena to come up with study propositions from organizational experiences and determine the potential of those thoughts in the given context. Few studies have explored the role of Big Data applications in the context of organizational competitive intelligence processes, and there is no proven empirical evidence on the implementation of Big Data methods in CI cycles. Therefore, this study arena is still in a nascent form, and case-study research is appropriate.

The organizations analyzed in this study belong to the Indian IT services, FinTech/finance and consumer goods sectors only. The purpose of choosing only three diverse organizations was twofold.

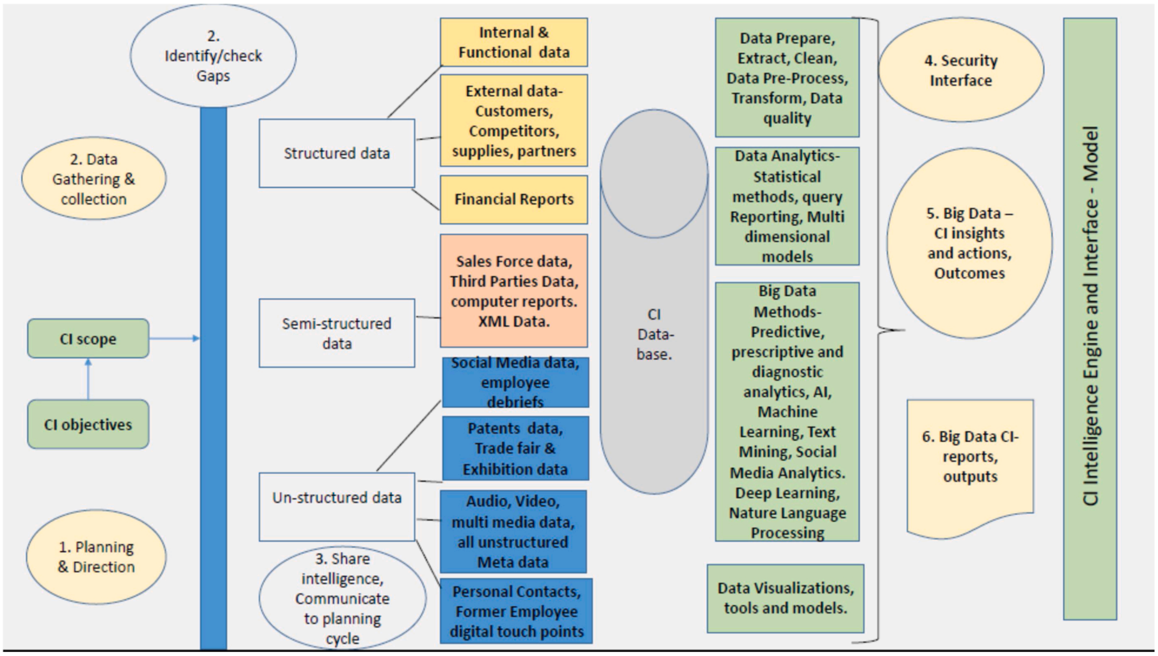

Fig. 1. Conceptual framework using Big Data methods for a Competitive Intelligence Process.

Analytical methods and their approaches in competitor analysis differ from organization to organization. Further, in sectors such as finance, IT, and consumer goods, although the nature of data and decision making differs, the approaches to gathering competitor intelligence in these Indian firms are quite similar. Different hierarchical levels, such as senior-level key professionals and managers with business development, strategy and planning, BI, market intelligence, product development, and domain expertise were chosen for the firms. The organizations and profiles were shortlisted on the basis of performance ranking and locations (See Appendix 1).

4.2. Data collection

Data collection was performed through interviews held in two phases: first, an initial data collection, followed by an in-depth data collection round. In the initial data collection, the research objectives were introduced to selected organizations. During in-depth data collection, copious focused interviews addressing the research questions and background information about industry, market, and firm specifics were conducted. Frequent discussions were held to articulate and debate core concepts and emerging theoretical frameworks. In total, 48 respondents from 21 companies were interviewed (12 members from each hierarchical level; the remaining ones are senior-level key professionals in marketing intelligence, business intelligence, market research, product development, business development, and strategy and planning from the organizations; see Appendix 1). Repeated semi-structured interviews with the same participants were conducted through on-site visits and conversations in order to ensure both the reliability and the clarity of the collected data. This diverse range of sources was designed to improve the likelihood of gaining a complete and accurate picture (Yin, 2008) as well as to provide textual accounts of debates and discussions and to strengthen confidence in the findings. Anonymity was ensured to all informants, and the interview questions are included in Appendix 2.

4.3. Initial Interviews

In-depth interviews of 60 to 90 minutes were conducted and follow-up visits were done. Interviews comprised 32 questions and were divided into three sections: general demographic information, knowledge of various CI activities, and knowledge of Big Data methods. Questions were aimed at establishing the information held by participants on various topics including their involvement with and knowledge about CI. The next section of questions dealt with various CI activities, stages of CI development, and CI information sources; the third section investigated analytical methods for data collection, use of Big Data software, decision support for CI, measurement of CI, Big Data approaches, etc. Participants were also asked to share their evidence and relevant experience. Care was taken during interviews not to point out any new information to respondents. Semi-structured interviews were the main data collection approach, followed by observations, literature review and secondary Internet data searches, which investigated a variety of data sources as secondary material for data validity, such as company websites, books, literature, PowerPoint presentations, product manuals and catalogs, promotional videos, and informal conversations. Furthermore, some of the selected organizations already had a functional basic business intelligence and analytics system when the study was conducted and were therefore in a position to understand the basics of Big Data and CI for generating strategic value. Interviews were carried out with three to four participants in each organization who were familiar with business intelligence and analytical systems.

As the interviews unfolded, it was discovered that practices within selected organizations were using basic business analytics methods and were not implementing advanced Big Data methods in CI cycles. *Are there any Big Data methods used during CI cycles? How are the methods practiced?* These questions were the starting point for the grounded theory study. It aimed to understand, first, *how the CI process was viewed, how organizational intelligence functioned in organization, what were the methods for distributing the CI intelligence, how they measured the effectiveness of CI, where and how the methods are incorporated, how Big Data methods are applied*, etc. It was hoped that such an understanding would help the study to see how the norms and practices of CI vis-à-vis Big Data methods related to building intelligence in CI.

4.4. An open beginning and interview questions

The approach enabled the researchers to ask questions and collect data on what happens if Big Data-based intelligence is built into the CI process and how people interact with such models and methods. Some of the initial research questions were:

1 Is a formal CI process used in the organization?
2 How is the "intelligence function" structured in your organization?
3 Does your organization use Big Data methods or models to generate CI? How do you handle diverse unstructured data?
4 What are the methods currently used to present Big Data tools?
5 Does your organization make use of software related to Big Data tools or any analytics software, and is there an awareness of machine learning or artificial intelligence tools for CI activities?
6 Which potential threats or opportunities can be identified effectively by the CI?
7 How is the CI implementation done in your organization? Do you maintain a dossier or database for each competitor?
8 What are the most important functional challenges impacting your company's competitive intelligence strategy?

4.5. Theoretical sampling data analysis

Grounded theory studies are characterized by theoretical sampling (Pagell & Wu, 2009; Yin, 2008), as recommended for any case-study research. This involves collecting further data in the light of categories that emerge from earlier stages.

4.5.1. Coding and constant comparative method

Through coding, the research defined what was happening in the data and began to contend with what it meant. In the initial coding phase, the research generated as many ideas as possible, inductively, from early data. In the focused coding phase, the work followed a designated set of codes. After the first few interviews, a large amount of data was collected along with many initial codes. These codes included explanations, and comments, and the viewpoints and opinions of very senior managers, including business development managers, on the basis of their experience and involvement with CI operations. Because some of the senior officials knew about CI practices and functions in general, they could relate to the departments responsible for CI processes; thus, the process of seeking evidence from them became focused. By comparing the information available and the codes generated against other codes, a clear differentiation in the category of "seeking focused evidence" was attained (e.g., gathering information on CI methods, practices and the analytical techniques used, etc.) and the relationships between codes were understood. Theoretical codes were produced based on the constant analysis and comparison of the codes generated. Making sense of the evidence and building knowledge was then done based on the theoretical codes. The codes captured the processes of CI that senior level officials follow, the methods for using CI effectively, and the job roles involved. An inductive approach was used to generate substantive codes from the data so that subsequent collection of data at the next level would provide insightful codes for developing the theory.

4.5.2. Memos

During the entire study period, extensive flowchart-based conceptual memos were written. After each interview, a memo was written reflecting on what had been learnt from that particular session. A note was attached on participants' experiences, views, and reactions. These notes were also used to systematically question some of the following interviewees. After a few interviews had been carried out, comparisons were made among the memos. This ensured that the ongoing work did not just build the code categories, but could further divide each category into many sections of subcategory. Through this, the diversity and difficulty of data were recognized, and homogeneous categories were controlled. Some conceptual memos were also written, based on the initial and later, focused codes. These memos were then used to record the experiences regarding the interpretation of codes (e.g., the researchers' thinking about how and when CI processes happen, how intelligence functions change in organizations, what methods influenced CI, etc.). In the memos, selected codes were also compared to find similarities and differences so that the researchers could add more in the ongoing interviews or discard redundant ones. At the end of the analysis, a tentative model was developed on the CI process and Big Data approach. This was expressed in both diagrams and memos, and was built around an essential set of absorbed codes and the demonstrated relationships among them.

4.5.3. Ongoing data analysis

Although there was a detailed provisional model of the steps implemented in the CI process, at this stage the research did not understand what Big Data methods were being used; new questions were added for the interviews to directly investigate evidence of intelligent methods in CI processes. Some of the further questions were:

1 *How do you process unstructured competitor data? Are Big Data methods applied in your CI process?*
2 *How do you collect external data for CI? How do you process external data for building Big Data models?*

4.5.4. Mapping theoretical memos and further refining the concept

After theoretical sampling, coding was begun theoretically. Flowcharts were then drawn up, along with data flow diagrams and written memos, providing a clear understanding of each concept that emerged from the process. Research findings constituted a theoretical formulation of the reality under investigation, rather than making it consist of a set of numbers or a group of loosely related themes. In the following section, we provide a comprehensive description of evidence received from the selected organizations on Big Data practices, as well as analytical approaches in corporate CI processes.

5. Research Findings

A first major research finding was the indication of a rather centralized, informal process as opposed to a clear formal structure for CI. Various interviewed executives admitted that they did not have a clear formal structure for CI but rather relied on a centralized informal process. Some firms had not labeled CI as a formal process. Others equated it to market intelligence. Another important related finding relates to building intelligence in the CI process. The interviewed executives felt that there were many apps to automate the social media search process for data nuggets from competitors. Some firms gathered information about competitors by asking their business colleagues while networking or socializing, individually or as a group. Some believed in asking their customers and clientele during social situations about competitors' services or products. The delving process is a critical input for building intelligence. However, owing to the current lack of application of Big Data methods to align with the CI structure, there is no defined standardized architecture or framework on Big Data value in CI processes.

This first research finding appeared as a major theme in interviews. For example, as participant 3 (age 57, gender male) described: "*The risks and opportunities seem to be too obvious to require a formal system in place, you see, we are in the business and know the dynamics in real time. We know our competitors and what they are up to, that is what we do all day when we network. To set up a system for what is so obvious seems a little far-fetched.*" In addition, another participant (age 47, gender female) stated: "*I had a discussion with the CEO about implementing an integrated CI system using Big Data. I presented data about how US companies are leveraging CI to enhance performance. However, he felt it was an added expenditure, and the whole bureaucratic setup would increase documentation load, so we are better off without a formal setup.*"

A second major finding indicated the use of basic tools for queries, as opposed to reliance on dedicated methods such as advanced machine learning. On one hand, the interviewed executives were aware of Big Data and their influence in businesses. However, some participants clearly admitted they did not have currently Big Data tools for coming up with valuable insights. For example, participant 16 (age 39, gender male) told us, "*People talk about Hadoop, Hive, even Excel to capture Big Data. But we do not have a clear understanding as to which would be the most suited tool for our firm. We are contemplating getting demos, so that we can choose the right kind of tool to capture data*." The selected organizations used basic tools such, as Microsoft Excel, SAP, or SAS for queries and reports. Most of the organizations considered in this study admitted to a paucity of efforts to use Big Data methods such as advanced machine learning, real time in-memory computing, and so on for building better intelligence in CI. The findings showed that the selected firms did not maintain a real-time CI database or a diverse data warehouse. These organizations had, however, signed up for the newsletters and surveys of competitors; pieces of information were collected at trade shows and through external domain expertise; but there was no Big Data tool available to integrate the information collected with information collected from regulatory agencies, industry cross-sector publications, and competitors' public relations information.

A third research finding deals with the challenges faced by firms, including a lack of staff proficiency, insufficient understanding of the Big Data approach, trustworthiness of data, and lack of process or domain skills. Another major challenge consisted of building models, since lots of fake information was available, both on- and offline. The major apprehension cited by these organizations was a lack among the present CI staff of experience, awareness, and knowledge of such Big Data in CI. The senior managers expressed trepidation towards developing, monitoring, and implementing counterintelligence tactics and dashboards for better CI. Table 1 provides further detail and related results. These findings were reflected across the interviews. First, participant 21 (age 44, gender female) stated: "*We hired IIM graduates specially to gather CI through Big Data. But they were not equipped with the right kind of analytic approach, and we let them go, they were pretty expensive, yet the insights were not coming.*" Second, another participant (age 58, gender male) observed: "*How can you trust the internet? The quality of data is seriously*

Table 1
Findings

CI METHODS USED	PERCENTAGE	RANK
Competitor analysis	58.8	1
Customer segmentation	52.9	2
SWOT analysis	47.1	3
Industry/5 forces	35.3	4
Financial analysis	29.4	5
Win/loss analysis	23.5	6
Benchmarking	17.6	7
Others	17.6	7
Scenario analysis	11.8	9
Data dissemination points	Percentage	Rank
Presentations/staff briefings	82.4	1
Printed alerts/reports	52.9	2
Newsletters	41.2	3
Company intranet	41.2	3
Central database	29.4	5
Potential threats/opportunities	Percentage	Rank
New customer/target audiences	76	1
New competitors	52.9	2
Customers' DEMANDS	41	3
Industry Competitors	23	4
Potential suppliers	17	5
Staffing options		Percentage
Project team in house/external		64
Project team/ employees		35
External consultants		5
SOURCES OF CI IN FIRMS	PERCENTAGE	RANK
Commercial databases	64.7	1
Industry experts	64.7	1
Customers	58.8	3
Publications (print/online)	52.9	4
Social media	17.6	5
Internal data	11.8	6
Company employees	5.9	7
Criteria for CI effectiveness	Percentage	Rank
New or increased revenue	35	1
New products or services deployed	34	2
Cost savings/avoidance	23	3
No measure used	20	4
ROI calculation	17	5
Big Data tools/Software tools used		Percentage
Yes		64.7
No		11.8
Challenges in adopting Big Data applications in CI	Percentage	Rank
Developing, monitoring, and implementing counterintelligence tactics	52.9	1
Capturing the competitive information held by the firm's employees	41.2	2
Developing an integrated competitive insights dashboard	29.4	3

questionable, and to make decisions based on such insights makes me skeptical." Third, another participant (age 46, gender female) stated, "*we use basic Big Data like analytics, competitor analysis, SWOT, segmentation analysis, 5 forces analysis; however, we have not used this in real time on larger data. We want to use advanced text mining, natural language processing, etc., which are all related to Big Data.*" (See Appendix 2.) Table 1 provides more detail.

Overall, the research findings provide a clear understanding that the firms are yet to consider Big Data technologies in CI processes; these results have contributed to start building the process for Big Data in organizational CI cycles.

Building on the research findings, a process model is proposed below. This process model aligns with the three-dimensional value framework for Big Data provided by Brinch (2018). The process model (see Fig. 2) provides an extension to the discovery process for various activities in CI cycles with respect to Big Data methods in CI cycles.

Building on evidence from both the interview findings and the process model, a new conjectural theory is constructed to assess the formal CI process and structure of intelligent functions in organizations. Based on the findings, the theory outlines that it is necessary to analyze the analytical capabilities of firms along with their CI needs. Some organizations may have extant analytical proficiency and skills, while some may not have. Similarly, some organizations may have a well-defined CI structure, while others may not have a formal structure. Hence, the CI requirements and the firm's analytical capabilities can be different from organization to organization. Based on the findings and the process model, Fig. 3 presents a conjectural approach to defining the analytical capabilities requirements vis-à-vis the CI requirements of firms.

The four segments highlighted above serve as inputs and feedback mechanisms for adopting Big Data methods in firms for better CI. The CI requirements and analytical needs defined above will give firms a perspective on their preparedness with respect to analyzing how their competitors are leveraging analytics and the opportunity to take capability-building measures to bridge the gap, if any exists.

6. Discussion

Earlier studies have not explored the role of Big Data methods in building effective CI in organizations. In this grounded-theory-based study, we have provided a good basis for understanding how firms

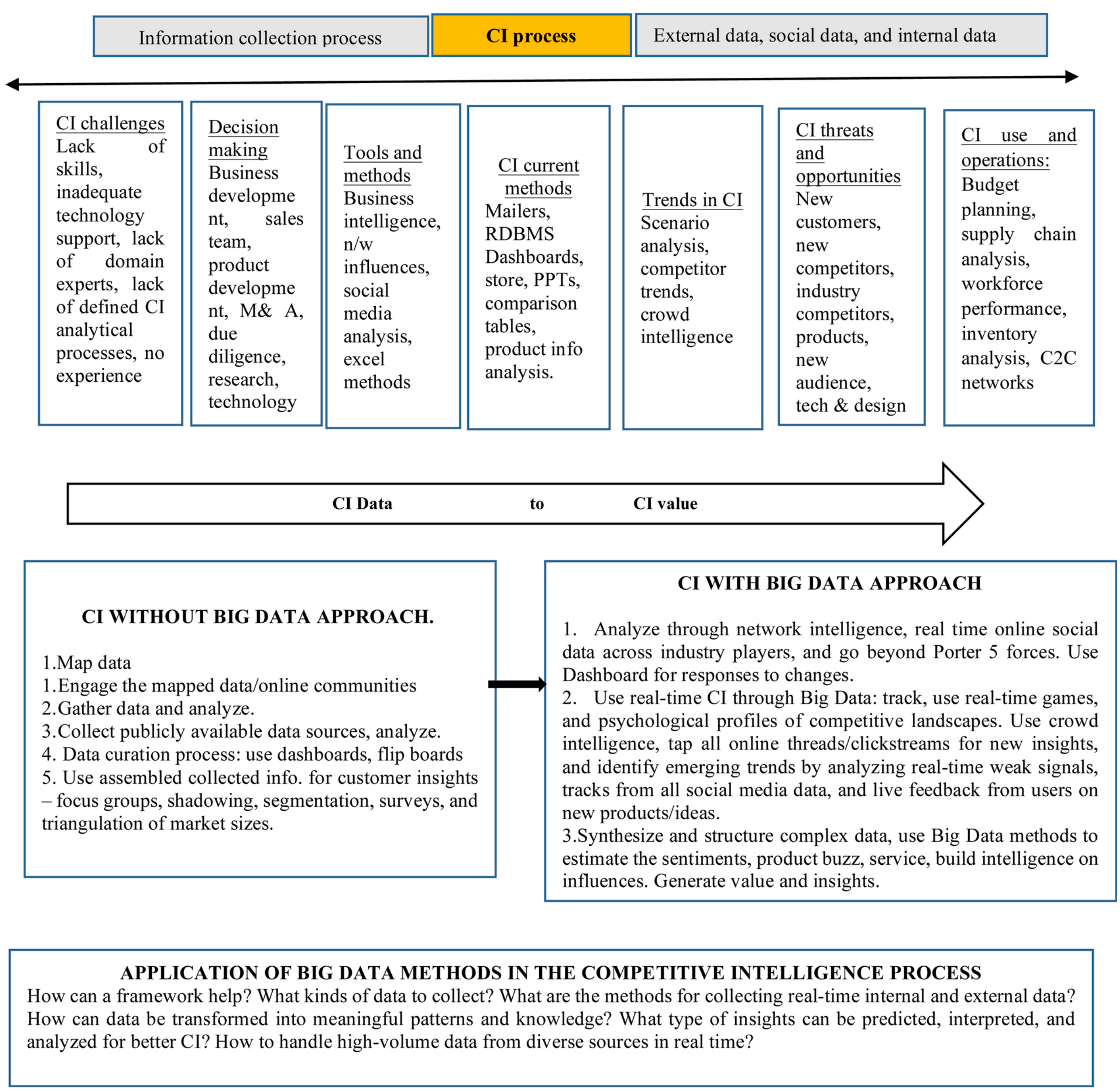

Fig. 2. Process model.

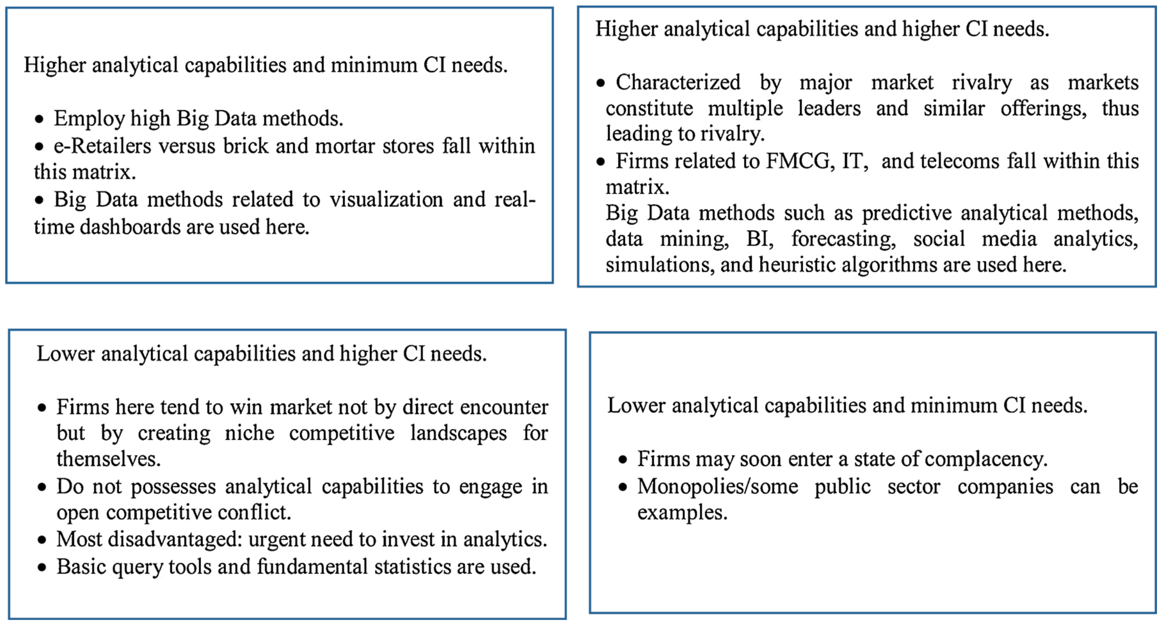

Fig. 3. Analytical capabilities and CI needs in organizations.

could improve their respective CI mechanisms through Big Data insights. This study has explored the impact of Big Data methods in CI processes, and how organizations can and do build CI. The research findings have shown that companies are yet to adopt Big Data methods having the desired impact in terms of CI, and Big Data methods were not used in CI intelligence processes even in large and well-established companies. These results are theoretically important given the need to have a better understanding of the impact of Big Data methods in building CI in organizations. Specifically, the results indicate that, while basic intelligence is acquired using MS Excel, SAP, or SAS for queries and reports, surprisingly, no CI database was maintained on a real-time basis. These results imply that, for building intelligence based on past data, current data, and future data, organizations need to extend their Big Data capability across all dimensions, and the study findings shed light on the benefits of adopting the framework for data consolidation, real-time intelligence, online tracking of competitors, and new insights into competitors' territories that have never previously been explored. To sum up, this study provides unique insights by investigating the mediating role of Big Data methods on organizational CI processes.

Our framework has implications for those business processes involved in various CI operations; it would be impactful for organizations, Big Data communities, and managers who use data (both operational and strategic). There exist lots of competitor information that could be gathered into a corporate database for CI analysis. Paying attention to competitors' advertisement zones may capture and communicate a great deal about the particular audience that competitors are trying to target and what particular products or services they are trying to promote. These data will be useful for organizations to introspectively view their own campaigns and promotions. The trick consists of collecting more data on competitor promotions to identify weaknesses by using basic Big Data methods directed at their marketing and find opportunities to crease new product or service segments. Regular visits to competitor spaces, blogs, social media postings, and websites for finding the rich mines of CI information towards leveraging current intelligence are needed. This enables firms to cross compare using analytics and check their working in order to displaying more ideas. Big Data analytics in general and web and text mining play vital roles here. Competitors' plans, their strategies, and their hiring and personnel patterns could easily be analyzed. There are many apps for automating the social media search process to obtain data nuggets on competitors.

Some firms do also gather information about competitors by simply asking their business colleagues while networking or socializing, individually or within groups. Firms also believe in asking their customers and clientele about competitors' services or products during social situations. The delving process is a critical input to the Big Data process to extract hidden, interesting business insights and may provide knowledge nuggets to help firms in understanding their own products. Being an actual customer to a competitor would yield more hidden information. This may involve organizations signing up for newsletters, surveys, etc. Using trade shows or talking to internal and external domain experts would also promote gathering additional CI information. This, again, is a valuable source for Big Data models and organizations need to maintain a clear database of all such collected information so that Big Data analytics can be applied for new product development or offering an enhanced service. The timely addition of information related to regulatory agencies, industry cross-sector publications, and competitors' public relations information would be an additional benefit to CI insights. However, a complete ethical procedure needs to be followed. During the interview process, many senior officials hinted at having hired people from competing firms, the sales team in particular to obtain additional horizontal and vertical leads. Unfortunately, companies do not maintain a clear database on whom they and the competitors are hiring. With LinkedIn analytics, there is a strong opportunity to tap the CI through a different lens. All the senior executives interviewed agreed that about 90% of the data in the world today was generated only in the very recent past. Big Data methods help with the analysis, since they translate millions of entries into valuable information through advanced analytical and mathematical algorithms and probability analyses. Diverse data were also collected from the profiles of competitors, product data, customers, new employees, and other sources such as corporate guidelines and policies.

The more organizations access competitor data, the more strategic advantage they gain. The principal outcome from CI is the capability to make forward-looking decisions using Big Data. Organizations are looking towards Big Data-fueled computing methods such as the IoT, intelligent personal assistants, machine learning, artificial intelligence, deep learning, smart robots, content analytics, neuro business models, etc. Such Big Data methods are going to reshape the way in which organizations look at CI in the near future.

6.1. Theoretical implications

Despite the fact that Big Data's characteristics, namely volume, velocity, variety, and veracity, act to give important data-driven insights and are critical for enhancing organizational competition (Ghasemaghaei & Calic, 2020), and strong evidence of Big Data disrupting tactical decision-making processes and impacting on strategic decisions within organizations (Merendino et al., 2018), many organizations nevertheless do not successfully leverage business outcomes through Big Data (Johnson, Friend, & Lee, 2017), and our research findings have identified challenges faced by organizations in this matter, which sheds lights on studies that have indicated that Big Data approaches may or may not improve business competition (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011; Merendino et al., 2018).

Despite the growing number of firms launching Big Data initiatives, there is still limited understanding on how firms translate the potential of such technologies into business value, as stated by Mikalef et al. (2019), who examined 175 strategic-level specialists regarding Big Data approaches and highlighted several challenges faced by organizations when orchestrating Big Data analytics. In order to avoid such challenges, recent studies have proposed approaches and sets of guidelines. Barchiesi and Colladon (2019), for example, proposed approaches combining text mining, social networks, and Big Data analytics for analyzing stakeholders' attitudes using twitter threads, and Müller et al. (2016) discussed the use of Big Data analytics as a strategy in information systems (IS) research and proposed a set of guidelines. In the same theoretical vein as those two studies, the findings of the present study have expanded our understanding of the role of Big Data in building CI within organizations.

The theoretical implications of our study include setting up a foundation, in terms of competitive intelligence, for Big Data and advanced technologies, which is extremely important. Building high levels of trust in CI is crucial in decision making given that the nature, type, quality, and content of data are sensitive and vary over time. Also, given that unstructured competitor data is very turbulent in the business environment, the CI matrix and framework can make a crucial strategic contribution to organizational success. Setting up business units to share information on competitors, customers, social media networks, and governance for CI may be a challenging task. Nevertheless, our research results have highlighted the relevance of Big Data characteristics for enhancing CI value. Our findings suggest that a conjectural theory is necessary to assess the formal CI process in organizations. This can serve as a valid guideline for organizations intending to maximize their CI value. It is also worth mentioning that generating larger data alone will not push firms to build intelligence. Some firms may not have analytics and some may lack a formal CI process. In this regard, it is worth noting that the number of organizations that are keen to invest in Big Data in next few years has fallen by 6 percent (Van der Meulen & Woods, 2015).

6.2. Managerial implications

Over the recent years, more and more organizations have started to capitalize on the significant use of Big Data and emerging technologies to analyze - and gain valuable insights linked to - decision-making processes. Interestingly, our study has indicated that Big Data Analytics is currently far from been used at its full potential in the area of Competitive Intelligence. Therefore, there is tremendous room for improvement for those organizations willing to take advantage of monitoring their respective competitors. Accordingly, with a view to build competitive advantage in such areas, all stakeholders involved in competitive intelligence activities may take into consideration the following managerial implications.

Firstly, our findings suggest a preference for a rather centralized informal process as opposed to a clear formal structure for Competitive Intelligence, leaders and managers willing to build Big Data Analytics-based Competitive Intelligence need to practice Big Data approaches by assimilating various facets of data sets, including both structured and unstructured sources, and using advanced tools to extract insights as mentioned for instance by Janssen, van der Voort, and Wahyudi (2017). In addition, leaders and managers willing to build Big Data Analytics-based Competitive Intelligence need to build and use Big Data personnel skills, based on Akhtar, Frynas, Mellahi, and Ullah's (2019) research findings which have shown that organizations utilizing Big Data personnel skills are more productive regarding business performances. Overall, stakeholders should consider building a Big Data culture, and should be familiar with Dubey, Gunasekaran, Childe, Blome & Papadopoulos's (2019) study that provides insights regarding Big Data culture.

Secondly, our findings clearly highlight the use of basic tools for queries as opposed to reliance on dedicated methods such as advanced machine learning, leaders and managers interested in building CI through Big Data approaches should consider it as a business project as opposed to an Information Technology project, which resonates with Sena, Demirbag, Bhaumik, and Sengupta (2017) research investigating two case studies on the impact of Big Data technologies on organizational strategies which showed that some firms do not think of Big Data projects as business projects but rather as Information Technology (IT) ones.

Thirdly, building on our findings which highlight some significant challenges that organizations are facing regarding the optimal use of big data analytics in building organization Competitive Intelligence. The stakeholders involved in Competitive Intelligence activities should acknowledge that collecting the "right" information about competitors may be a challenge, and Big Data could resolve this challenge using tools such as text mining or deep learning, and NLP would bridge the gap of understanding reports, documents, and clickstreams of diverse vernacular competitor data, dealing with open-source frameworks (e.g., Hadoop and MapReduce), and taking care of voluminous distributed data. Moreover, stakeholders involved in Competitive Intelligence activities should keep in mind that Big Data approaches have encouraged organizations to restructure their Competitive Intelligence processes and this has potential impacts for strategic decision making. Indeed, some studies suggest that organizational board meetings are trying to refrain from top-down planning and are willing to process larger digital data sets to combine the companies' real-time financial strategies with their competencies for better intelligence (Camillus, 2008).

Finally, with a view to ease the process of developing Big Data Analytics-based competitive intelligence, all stakeholders should consider our conceptual framework for using Big Data methods for a competitive intelligence process as a starting point. In this regard, our study provides a context for developing Big Data frameworks and process models for Competitive Intelligence in organizations.

7. Limitations and Future Research Directions

Several limitations need to be acknowledged in terms of theoretical sampling and the associated emerging insights. First, the research findings are restricted to the respective identified business sectors – that is, IT, consumer goods, and FinTech companies only. One future research direction could be a cross-business market analysis of CI regarding the adoption of Big Data. Second, McAfee and Brynjolfsson's (2012) study emphasized the importance of Big Data applications for profits and increased productivity without investigating the intrinsic value of each business report. The objective should be to understand CI in each business process and the appropriate Big Data approach for it, and this gap can provide a significant area for further research. Third, not many company officials disclose their sensitive information regarding CI; in our study, it was difficult to convince officials to share CI information despite repeated visits. Future research studies could focus on CI and identify intangible factors, such as social norms, socioeconomic status, gender roles, ethnicity, religion, and culture and how they affect Big Data adoption in CI. Building on the findings of our study, future research is required in a field where *"(…) the body of research into Big Data so far lacks an academic work capable of systematising the organizational theories supporting Big Data domain.*" (Camargo Fiorini et al., 2018, p. 112). Overall, future research opportunities are abundant as the landscape of CI and data analysis is transforming with Big Data.

8. Conclusion

The more companies know competitor data, the more strategic advantage those companies gain. This fusion of Big Data and analytics can help in creating a system for CI analytics that leverages advanced analytics to improve the accuracy of traditional CI techniques. The present study has contributed in understanding the value of Big Data approach for a successful CI cycle. The framework synthesized a large body of literature, in which much emphasis was directed at the unique set of characteristics of Big Data. This approach, it is strongly believed, will trigger data management in CI processes. The new trend that has already gained momentum is data as a strategic asset. In the era of global cyber-attacks, online fake news, and data diversity hassles, organizations have two choices: Continue to be skeptical on Big Data assets, or embrace Big Data nuggets to discover new managerial insights.

AUTHORSHIP STATEMENT

All persons who meet authorship criteria are listed as authors, and all authors certify that they have participated sufficiently in the work to take public responsibility for the content, including participation in the concept, design, analysis, writing, or revision of the manuscript.

Furthermore, each author certifies that this material or similar material has not been and will not be submitted to or published in any other publication before its appearance in the International Journal of Information Management.

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