Big data and firm marketing performance: Findings from knowledge-based view

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Abstract

A universal trend in advanced manufacturing countries is defining Industry 4.0, industrialized internet and future factories as a recent wave, which may transform the production and its related services. Further, big data analytics has emerged as a game changer in the business world due to its uses for increasing accuracy in decision-making and enhancing performance of sustainable industry 4.0 applications. This study intends to emphasize on how to support Industry 4.0 with knowledge based view. For the same, a conceptual model is framed and presented with essential components that are required for a real world implementation. The study used qualitative analysis and was guided by a knowledge-based theoretical framework. Thematic analysis resulted in the identification of a number of emergent categories. Key findings highlight significant gaps in conventional decision-making systems and demonstrate how big data enhances firms' strategic and operational decisions as well as facilitates informational access for improved marketing performance. The resulting proposed model can provide managers with a reference point for using big data to line up firms' activities for more effective marketing efforts and presents a conceptual basis for further empirical studies in this area.

Keywords: Big Data Analytics; Artificial Intelligence; Marketing Performance; Knowledge-Based View

1. Introduction

In recent years, industry 4.0 have emerged as the most discussed concept across academia and in industry. Industry 4.0 concept rely heavily on the effective use of emergent digital technologies (i.e., Big Data and AI) to enhance business performance (Frank et al., 2019; Kristoffersen et al., 2020; Reischauer, 2018). Industry 4.0 technologies for instance actuators and sensors also add towards the development of big data information assets, which firms can use for value creation (Kar and Dwivedi, 2020). Industry 4.0 provides a particular drive and emphasizes on these areas where the functions of the firms might better hold with recent era technologies for instance IIoT, IoT, cloud computing, big-data analytics etc. Considering as an illustration, cloud based tools combined with data analytics technique may optimally assist in firm's resource planning (Khanzode et al., 2021). The German federal government established in the year 2011, the term Industry 4.0 as an important aspect of country's high-tech plan (Xu et al., 2018) to improve its industrial capacity via digitally controlled industrialization. Industry 4.0 (I4.0) is a proficient approach to affect entire business procedures and performances (Luthra et al., 2021). Indeed Raut et al. (2021) emphasizes on the connection between big data analytics and sustainable business performance from a LARG (Lean, Agile, Resilient, and Green) perspective. This digital revolution has resulted in a considerable impact on business processes by enhancing the veracity, volume, and variety of information produced from unstructured data, which has given rise to an innovative era in which business performance is reliant on data-driven decision making capabilities (Gupta, Kar, Baabdullah & Al-Khowaiter, 2018). The support of decision-making is a crucial concern for marketers, via offering insights to aid in replying important questions for instance: what is most fitted product for a particular market; how to promote that product in such a market and many more (Amado et al., 2018). Given these ideas, it is undoubted that Marketing has become from the start a field for experimentations with Big Data advances (Bendle & Wang, 2016).

During last few decades, the organizational environment has undergone major revolutions in its key activities, consisting of marketing, product planning, product development, procurement, manufacture and distribution, etc. All these changes have been underpinned via make use of disruptive Industry 4.0 technologies, for instance big data, redistributed manufacturing, preservative manufacturing, automated robots, digital twins etc that have intensely transformed organizational processes and operations (de Sousa Jabbour et al., 2018; Luthra and Mangla, 2018) and thus resulted into new advanced and developed systems (Grover and Kar, 2017; Li, 2018; Sung, 2018). Industry 4.0's advanced IT systems are driving the organizational setting forward that has shifted from the "steam engine era" (Industry 1.0) to the electrical energy use (Industry 2.0) and electronics and IT application (Industry 3.0). Industry 4.0 supports in converting an organizational system into a smart system, which include some sensors and inter-related devices (Tu et al., 2017). At present, organization managers, manufacturing engineers and professionals have revealed attention towards integrating modern technical developments for effective and successful running of an organization (Buer et al., 2018; Müller et al., 2018b).

However, industrial professionals and practitioners have exposed low attraction towards the technical development of processes and operations in their Industry 4.0-based operations (Müller et al., 2018a, 2018b). Accordingly, industry managers have felt the need of thorough research in managing organizational systems through the automation and digitalisation of processes and operations i.e. Industry 4.0 (Hofmann and Rüsch, 2017; Jabbour et al., 2019; Chen et al., 2020). Many businesses are devoting extensive spending toward big data analytics (BDA) for rapid decision-making and enhanced marketing performance, particularly in customer behavior assessments (Shirazi & Mohammadi, 2019). Organizations are increasingly recognizing the importance of big data for ensuring profitability and driving sustainability (Upadhyaya & Kumar, 2020). Beyond its capacity to manage data storage issues, big data has greatly facilitated decision-making processes (Nutt & Wilson, 2010), and BDA has been shown to improve firms' profitability, operational efficiency, and marketing performance in both short- and long term (McAfee & Brynjolfsson, 2012; Shen, Choi, & Chan, 2019). An organization's BDA capability directly and indirectly affects firm performance (El-Kassar and Singh, 2019; Rialti, Zollo, Ferraris, & Alon, 2019; Upadhyay & Kumar, 2020). Technological factors (e.g., perceived benefits, complexity, technology resources, data quality, and integration) have the highest influence on big data adoption and performance (Yadegaridehkordi, Hourmand, Nilashi, Shuib, Ahani & Ibrahim, 2018). Customer knowledge has become a keystone of the virtuous circle of benefits that big data confers upon marketing performance (Kar & Dwivedi, 2020); big data technologies and advanced analytical techniques have reconfigured marketing approaches to provide significant insights into customers and obtain greater customer responsiveness (Upadhyaya & Kumar, 2020).

The vast use of IT systems in today's industries and enormous availability of recent technologies for instance Big Data, Artificial Intelligence, Cloud computing and of course semantics, promise to provide the added value, which eventually will build up a new inter-connected factory (Gupta et al., 2018; Luthra et al., 2020). Several arguments have been made in diverse forums during the past few years regarding Industry 4.0 ideas and potential ways to execute them in today manufacturing setting. The majority of managers of big companies considered that this recent Industrial transformation must be applied quickly in their organizations to improve performance (Merendino et al., 2018). Whereas, the truth about most of these companies is that they have to tackle the presence of legal systems and rigid solutions that in leading scenario might just offer restricted inter-connectivity via presenting quite basic data logs in sometimes faraway formats. Thus, in this type of situation, some relevant questions are to be answered. Possibly among these questions, the first and foremost to take place in mind could be:

Q1: What is the current status of the company? - or, in which phase of the advancement in relation to the upcoming industrial revolution could the company be suited?. Thus answering this question reveals an initial place in the process of considering strategies for bridging the available learning and executes gaps.

Q2: What do I have to consider to execute the upcoming industrial revolution in the company? – Answering this question must automatically take towards new normative, recent security and data storage approaches etc. It might also present important information where the essential components are already here but emerging one, so have to decide about which ones are not important and which ones are not present.

Q3: How do I involve decision makers, experience and finally decriminalise the company knowledge which is at present in the hands of few experts in company? – This question will guide in connection with a recent paradigm move where such context specific know-how, user experience and basically conceptual semantics involved in company's processes and the similar must be considered if a company intends to make its shift towards latest industrial revolution – Industry 4.0. The present paper mainly emphasizes on the last question. In case of this question, the conceptual and theoretical aspects related to latest industrial revolution–Industry 4.0 implementation are to be mainly covered. Accordingly, this paper discusses a framework on how knowledge based view came into existence in context of aforementioned paradigm move and consider the close case of Industry 4.0 as a triggering object underneath. In this paper, we mainly emphasize specifically in the proposed theoretical model on marketing performance using BDA with its key components required for the enhancement and support of Industry 4.0 with knowledge based view.

Drawing on a knowledge-based approach, this study builds on three analytical lenses that can be used to examine how a firm's marketing performance is associated with big data. Firstly, we consider big data as a knowledge point for an organization's board; secondly we expect that this point, albeit essential, is not enough on its own, and its value can differ based on cognitive and dynamic competencies; and thirdly, we introduce behavioral aspects to understand businesses and their performance, specifically in terms of marketing.

The remainder of this paper is structured as follows. Sections 2 and 3 present background discussions on BDA and marketing performance, which are integrated into a theoretical framework in section 4. Following a description of our research methods in section 5, we integrate emergent themes identified via a thematic analysis of 10 semi-structured interviews with a systematic approach to develop a conceptual model in section 6. Lastly, we discuss about the results along with conclusion, limitations, and potential future research on big data in relation to firm's marketing performance.

2. Review of Literature

2.1 An overview to Big Data

Big data refers to the dynamic, large, and disparate volumes of data being created by people, tools and machines both inside and outside a company (Gupta, Kar, Baabdullah, & Al-Khowaiter, 2018). McKinsey Global Institute (2011) defined big data as *"datasets whose size is beyond the capacity of typical database software tools to capture, store, manage, and analyze data."* These datasets are too large and complex for traditional data management tools to efficiently process, so they must be handled using innovative technologies (Big Data University, 2016; Tykheev, 2018). As Gantz and Reinsel (2011) described, big data technologies are *"a new generation of technologies and architectures, designed to extract an economic worth from very large volumes of a wide variety of data, by enabling high-velocity capture, discovery and/or analysis."*

According to earlier computing theory, the concept of big data rests on four dimensions: volume, velocity, variety and veracity (Gudivada, Venkat, Baeza-Yates, & Raghavan, 2015; O'Leary, 2013; Sagiroglu & Sinanc, 2013; Singh & Singh 2012). Later, "value" was added as a fifth dimension that specifically corresponds to the collection and use of customer information (Tykheev, 2018).

A fundamental element of big data theory, *volume* represents the large quantities of data collected for processing and analysis. This dimension marks the replacement of traditional storage and processing capabilities or tools, which cannot effectively scrutinize and interpret such large data collections, by new, high-powered processing technologies (Girard & Allison, 2008). *Velocity* corresponds to the rapidity with which data are generated, processed, and transferred in order to make data clean and available for real-time decision-making (Chiang, Goes, & Stohr, 2012), whereas variety illustrates the unprecedented diversification of Internet and digital data domains and types, including structured, semi-structured, and unstructured data (Arbesman, 2013). *Veracity* refers to the need for high quality data for coherent analysis that yields valuable and meaningful results (Higdon et al., 2013). Finally, *value* is the most important dimension for companies, as it refers to the transformation and monetization of customer data to inform business strategy and marketing (Joseph & Johnson, 2013). As big data theory has evolved, more dimensions, such as variability, visualization, virality, have also been added to the theoretical framework (Clark, 2018).

2.2 BDA and marketing performance

In order to study big data technologies and their impacts on marketing performance, it is important to address the subject of BDA, which is at the heart of this research. Chahal and Gulia (2016, p. 2) define BDA as *"analytical methods of big data, systematic architecture of big data, and big data mining and software for analysis. Data investigation is the most important step in big data, for exploring meaningful values, giving suggestions and decisions."* The fundamental purpose of BDA is to explore data and identify patterns and relationships that are imperceptible at first reading to gain advanced insights about users. With the development of data sciences, businesses have access to a precedented number and range of analytics tools that can be used for both marketing and research and development purposes (Mayer-Schönberger & Cukier, 2013).
BDA also refers to related technologies for data enhancement and visualization such as big data mining and business intelligence (BI). *Data enhancement* is a technical synonym for *data*

valorization from a computing perspective. As Mark and Douglas (2012, p. 5) described, *"big data is high-volume, high-velocity and/or high variety information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, [visualization] for decision making, and process automation."* According to them, BDA are based on statistical methods, forecasting, regression analysis, database querying and data warehousing. Such tools are available in the form of analytical software or internet-based cloud computing platforms for data storage and processing (Su, 2018). An integral part business intelligence, data visualization refers to a set of analytical techniques and tools that provide coherent, relevant, and exploitable information for executives and other managing partners to improve and optimize business decisions and performance.

Altogether, BDA provides a comprehensive framework for data analysis for the benefit of business decision-making process. As data analytics develop and expand, new technologies and approaches have emerged to supplement existing methods of learning from digital information. For example, artificial intelligence technologies are self-learning programs that follow specific protocols to independently learn from data-sets. Based on the information extracted from the data, AI programs are capable of generating predictions, segmentation, optimization, recommendations, and customization of multiple actions for clients. These operations are carried out by cross-referencing millions of pieces of data emanating from the entire purchasing journey of each consumer (Lexcellent, 2019).

Machine learning and data mining are AI-based technologies associated with data sciences. Companies can use data science to increase turnover, reduce costs, and better understand customers in order to establish targeted marketing strategies (Ahlemeyer-Stubbe & Coleman, 2014).

Customer knowledge (CK) is a key element in the realization of a marketing strategy. CK refers to *"the combination of experience, value and insight information which is needed, created and absorbed during the transaction and exchange between the customers and enterprise"* (Gebert, Geib, Kolbe, & Riempp, 2002, p. 110). Businesses now have the technological and human resources to collect and interpret users' data to deepen their knowledge of customers characteristics, behavior, demographics, and purchasing history. Such knowledge is generated during customer interactions such as purchasing, customer relation management, operations, and after-sales services as well as external sources. Such knowledge is generated to help companies satisfy their customers' needs and entails internal management processes of collecting information about products and services and matching those with customers' requirements and to enhance marketing and customer relationship management (CRM). Customer knowledge also refers to consumers' ability to develop expertise when utilizing a service or product and therefore serve as equal partners in the development process. When all of these forms of knowledge are combined, a company can develop a strong competitive advantage and improve its CRM (Garcia-Murillo & Annabi, 2002).

In order to successfully target customers, the segmentation – targeting – positioning (STP) enables companies to emphasize the strength of their products, the value proposition, or the needs of their customers (Gibbert, Leibold, & Probst, 2002; Hanlon, 2018). The STP process can be optimized using data analytics to conduct in-depth studies of customer knowledge.

Today, customers tend to have access to wide range of information about products, which makes it difficult to draw their attention and thereby necessitates the customization of marketing throughout the purchasing journey. Customized or personalized marketing refers to a strategy whereby a business leverages the analysis of customer data to offer a message or a product that targets the customer's needs and interests. In marketing research literature, this strategy is also known as one-to-one marketing (Wind & Mahajan, 2001). Customization entails using descriptive data or observing customers' behavior to efficiently and effectively draw their attention towards advertising or marketing messages.

Over the years, customized marketing has developed to such an extent that some researchers have redefined it as *customerization* (Wind & Rangaswamy, 2001). Craig R. Barrett, the former CEO of Intel Inc., defined customerization as identifying and helping what you recognize as your most favorable customers. Altogether, this contributes to the optimization of CRM; businesses analyze and manage customers' data throughout the purchasing and after-sales processes with the aim of improving relationships with consumers and thereby increasing retention rates and sales (Shanmugasundaram & Srilekha, 2017).

Improvements in CK techniques have provided businesses with the ideal information for designing an optimized user experience (UX), also known as the customer experience (CX). SAS (2019), the world's leading firm in software publishing and analytics, defines the customer experience as "your customers' perceptions – both conscious and subconscious – of their relationship with your brand resulting from all their interactions with your brand during the customer life cycle." Indeed, CX encompasses all of the emotions and feelings experienced by a customer before, during, and after the purchase of a product or service, which are used to inform customer experience management (CXM), which is *"the practice of designing and reacting to customer interactions to meet or exceed customer expectations and, thus, increase customer satisfaction, loyalty and advocacy"* (Gartner, Inc., 2019). A relatable concept applied in digital marketing is the digital customer experience (DCX) or online customer experience (OCX), which can be defined as *"the combination of all digital interactions a customer has with a brand. This can range from browsing a brand's website to interacting with the brand on social media"* (Shanahan, 2018). Sarathy (2019) proposed that a successful DCX must follow the rule of the three Cs, namely consistent, compelling and candid. All in all, the in-depth study of customer knowledge enables companies to personalize their messages and CX throughout the customer lifecycle to influence purchasing decision-making, satisfaction, and loyalty.

3. Theoretical framework: how big data affects marketing performance

This study developed a research approach founded on a knowledge-based perspective to explore the implications of big data for strategic marketing decisions. With the significant understanding of the function of knowledge in big data plan, execution and utilization, it becomes completely obvious that knowledge management should consider a most important organizational job in the management and governance of the use of big data in an organization situation (Toro et al., 2015). Knowledge management has the conceptual base and practical understanding to determine what data are required for the organization to run resourcefully and successfully, how those data could be analysed to present useful information for organization developments, decision making and how to build up knowledge base feedback loops so that amendments in data compilation and examination are prepared in response to transforms in business environment, both inside and outside. We follow McAfee and Brynjolfsson's (2012) view of qualifying big datasets through high levels of variety, volume, and velocity. As such, big data is described by size of the respective datasets and the challenges they represent for computing power (Erevelles et al., 2016; Fosso Wamba, Akter, Edwards, Chopin, & Gnanzou, 2017; George et al., 2016). To discharge the plurality of knowledge-based view, the current study explores the main aspects of knowledge at three dissimilar levels: the individual level (managerial/ directorial cognitive competencies); the board level (behavioral aspects); and the stakeholders' level (stakeholders' dynamic competencies). These points of view are integrated into a theoretical framework to explicate the precursors and outcomes of knowledge. The capacity to employ as main resource influences the board's decisions and actions (Amit & Schoemaker, 1993), and the literature acknowledges that in today's turbulent business environment, firms must constantly develop and revamp their existing knowledge in order to react rapidly to outside forces (Lin & Wu, 2014; Wu, 2010). As a typical resource, knowledge provides a firm with the tools to establish the *"basic foundations to renew or re-configure its resource base"* and construct new competencies (Côrte-Real et al., 2016, p. 380).

At the individual level, directors and managers aim to build up their intellectual models and abilities or cognitive competencies to identify, analyze and change situations (Helfat & Peteraf, 2015). This cognitive practice has been described as "cognitive complexity" (Schneier, 1979), and the literature specifies that it can initiate cognitive biases resulting in outdated thoughts and cognitive dissonance or contradictory ideas (Amit & Schoemaker, 1993; Brennan & Conroy, 2013; Carpenter & Fredrickson, 2001).

At the board level, cognitive complexity is grounded in practices (Grant, 1996). Practices consist primarily of unspecified and difficult to codify knowledge (Van Ees, Gabrielsson & Huse, 2009), which is manifested in behavior that is studied and replicated (Winter, 2003). In addition, board-level practices are related to individual-level cognitive competencies. Routines *"conserve the cognitive abilities of board members and […] direct attention to selected aspects of identified problem situations; […] they also create decision-making biases"* (Van Ees, Gabrielsson & Huse, 2009, p. 312). When investigating how boards process big data, it is necessary to think about their decision-making behavior. Kahneman (2011, p. 12), asserts that *"no matter how complex, refined or available data may be, decision-makers are unlikely to fully consider it, and so often make inaccurate decisions."* Thus, a knowledge-based view is undergirded by the perspective that corporate boards utilize reserves of knowledge and competencies to make decisions (Balogun & Jenkins, 2003).

At the stakeholder level, firms need dynamic competencies such as the capacity to secure the latest and largest amount of knowledge that will enable decision-makers to practically tackle environmental changes and predict stakeholders' requirements (Oliver, 2016; Reeves & Deimler, 2011). As the analysis of big data fuels innovative approaches to environmental developments, its utilization may enhance dynamic competencies by supporting decision-makers in being more reactive and adaptive to environmental shifts (Erevelles et al., 2016). Accordingly, companies need to *"integrate, build and reconfigure' competencies to meet the environmental changes big data highlights"* (Teece, Pisano, & Shuen, 1997, p. 515).

This paper emphasizes a key research gap identified by McAfee and Brynjolfsson (2012) and George et al. (2016) concerning how big data affects decision-making. Drawing on a knowledge-based view, we focus on three key analytical lenses that can be used to study how big data analytics influence a firm's marketing performance. This study proposes that: (1) big data is a knowledge point for boards; (2) however, this aspect, even if crucial, is not sufficient and may vary in value based on "cognitive" and "dynamic" competencies; and (3) the behavioral aspects of big data can be examined to understand a company's marketing strategy and performance.

3.1. How are big data technologies used to enhance customer knowledge and targeting strategies?

3.1.1. The role of BDA in the in-depth study of customer knowledge

Tykheev (2018) defines BDA as dynamic, large, and disparate volumes of data created by people, tools, and machines both inside and outside a company. These datasets are so large and complex that processing requires innovative, high-powered technologies. Technically, big data is used through various methods and analytical tools in order to store, process, and draw upon valuable information from unstructured datasets. In the fields of marketing and business management, big data technologies have ushered in a revolution in computing algorithms and data analytics. BDA are changing how businesses analyze their knowledge of customers, increase customer responsiveness, and gain insights into customer's behaviors (Chen, Chiang, & Storey, 2012).

3.1.1.1 The role of BDA in targeting customers

Marketing strategies are mostly based on the knowledge that a firm has acquired about its customers, which is used to identify those individuals to which the product or service is most likely to appeal and sell. Thus, it is crucial for firms to establish a strong and coherent segmentation – targeting – positioning (STP) process (Gibbert et al., 2002). As mentioned in section 3, segmentation entails dividing a target market into homogeneous and meaningful groups who share the same responses to specific marketing actions or product offers. After identifying segments, a marketer targets those consumer groups by evaluating the correspondence between each segment and specific products or brands to determine the potential for growth over time and market accessibility (Yi, 2017). Due to the deepening of CK by big data technologies, marketers can obtain all of the information they need to develop a successful STP approach and thereby guide their overall marketing strategy.

3.1.1.2 How does big data make STP more accurate?

BDA provide marketers with valuable information concerning customer knowledge that enables them to identify the customers who will be attracted and satisfied by specific products or services. Thus, marketers can elaborate a stronger segmentation of the targeted market and ensure not to avoid shortfalls due to marketing errors (Hermans, 2016; Lichtle & Ferrandi, 2014). Therefore, marketing professionals can target precisely potential customers and avoid shortfalls (Lichtle, Ferrandi, & Lévy, 2014). Customer knowledge technologies help reinforce brand positioning based on the analysis of customers' needs and expectations (Camilleri, 2018), thereby enabling a firm to determine what information to provide in order to convert individuals into customers and retain them over a long term. To conclude, big data technologies contribute to more effective marketing strategies, particularly STP, and thereby help firms avoid shortfalls and maximize their resources and profits.

3.1.1.3 The concept of re-targeting

Even if a STP strategy is successfully implemented by marketers, some targeted consumers may not be converted into customers. In such cases, big data technologies can help marketers to *re-target* those consumers. Re-targeting is a marketing process that generally entails targeting an individual who has visited a website but has not made a purchase (Bathelot, 2017). This practice is most commonly applied in the field of digital or e-commerce marketing (Hua, 2019). Indeed, a prospect who has consulted one or more product catalogues without validating the purchase is subsequently exposed to customized advertising highlighting the initially consulted product or service (Mercanti-Guérin, 2013).

From a data science perspective, big data technologies help identify individuals who need to be retargeted and collect information that can be used to customize a marketing message (Pegoraro, 2017). This process is more commonly accomplished through the insertion of tracking cookies provided by the big data-based re-targeting system to create re-targeting contact lists ('How Retargeting Works', 2012). Targeted incentives to revive a consumer's initial interest in a product are offered based on big data-based recommendation systems and a real-time analysis of the online customer's behavior and online history (Yang, Huang, & Tsai, 2015).

3.2 How are big data technologies beneficial to customization?

3.2.1 Big data for marketing customization

In the digital era, one-to-one or data-based marketing emphasizes the personalization of messages and offers for one single consumer. Supported by the progress of big data technologies and analytics, customized or personalized marketing has become the keystone of relational or strategic marketing activities (Wind & Mahajan, 2001). Indeed, the customization of marketing messages and products are the two main fields of application for big data technologies. Not only will customization impact the content of marketing messages and advertising, but it will also influence the way that products are suggested to customers.

3.2.2 Content marketing: the optimized customization of marketing messages

Using BDA, marketing and data professionals can collaborate to carry out complex and accurate analyses of customer data in order to provide a customized marketing message. Kose and Sert (2016) explain that in practice, Big data technologies collect users' data and monitor the evolution of their interests in order to identify key trends. This approach is directly linked to *content marketing*, which entails creating and distributing valuable, relevant, and useful content in a consistent way to attract and acquire a clearly defined audience with the goal of transforming strangers into prospects and customers (Tracy, 2014). Tracy (2014) defines the purpose of Content Marketing as being to attract and retain customers by permanently creating valuable content with the intention of changing prospects' behavior to the company's advantage. When applied to content marketing, BDA can use data scraping to find and collect information from customers' online articles, blog posts, social networks, forum discussions, e-commerce platforms, and other sources (Cheney, 2015). Using these new marketing tools, a company can identify information, questions, or comments from customers about its products, and marketers can create and distribute ROI-effective content that is customized according to the customers' needs (Marion, 2001).

3.2.3 Real-time marketing

Real-time marketing and *native advertising* are additional innovations in big data technologies in the frame of content marketing (Liu, Soroka, Han, Jian, & Tang, 2020). Real-time marketing entails instantaneously analyzing data on market trends or customer behaviors to enable more rapid decision-making. Big data technologies utilize BDA to collect and analyze online customers' data, which product recommendation engines then use to generate real-time suggestions as soon as a customer enters a merchant website (Briggs & Walker, 2016). Thus, real-time marketing enables merchants to establish strong links with customers without disrupting their browsing experiences (Marks, Grimm, & Campbell, 2019).

In a nutshell, big data technologies have a strong impact on content marketing and marketing performance. BDA can extract and analyze data from consumers' online browsing and purchasing history and thereby provide an in-depth about their needs, based on which marketers can create and distribute customized content and ultimately increase their ROI. BDA are similarly applicable to advertising that displays personalized information about a product.

3.2.4 Personalized marketing and product offerings

Marketers also rely on big data technologies to personalize their offers through similar analytical processes as those mentioned in the previous section. Personalized marketing enables the customization of offers to enhance sales results (Jones, 2002). Customization is made possible through the collection of customers' personal data, (online) cash receipts, product returns, loyalty cards, and other information from physical or online shops and other websites, which big data technologies use to analyze and provide insights into which types of products or services meet a high demand according to various criteria (Anshari, Almunawar, Lim, & Al-Mudimigh, 2018).

Customization opens new business opportunities in the field of personalized marketing, particularly *product recommendation engines* (PREs), which are data filtering systems that classify objects according to their relevance to the user. PRE technology builds a pattern of preferences to predict the *score* that the user would assign to each object, and the highest-rated object is offered as a final recommendation (Olcya, 2018). By leveraging big data technologies, marketers have the ability to analyze customer data and predict which product is most likely to be purchased or offer items similar to those that resulted in previous purchases (Sudheshna, Sri, Indraja, & Adinarayana, 2017). Marketing professionals rely on PRE to provide responses that target consumers' specific needs and thereby ensure a more positive shopping experience as well as increase sales and consumer loyalty (AntVoice, 2014).

To sum up, big data technologies enhance the customization of product offerings. Firstly, the combination of big data and personalized marketing enables marketers to customize product offerings based on in-depth analyses of customer data and thereby increase the quality and relevance of their offers. PRE ultimately helps to increase sales and customer loyalty by providing suggestions that truly meet consumers' needs.

3.3 How is big data used to enhance the customer experience?

Customer experience refers to consumers' conscious and subconscious perceptions of their relationship with a brand based on all their interactions with it during the customer life cycle (SAS, 2019). CX is managed through customer experience management, which is the practice of designing and reacting to users' interactions to meet or exceed expectations and thereby increase customer satisfaction, loyalty, and advocacy (Gartner Inc., 2019). In digital marketing, this is referred to as the digital customer experience, which entails compiling and combining all of a consumer's digital interactions ranging from browsing a brand's website to interacting with it on social media (Shanahan, 2018). The resulting customization of offers and recommendations influences customers' purchasing decision-making, satisfaction, and loyalty.

3.3.1 How does big data optimize CX to make the customer feel unique?

More and more companies rely on big data technologies to enhance CX as a means to increase customer satisfaction and engagement. BDA are well known for their capabilities not only to process and analyze customer knowledge, but also to understand customers' feelings and make emotional connections. Indeed, how a customer perceives a brand plays an important role in his/her relationship with a business (Gebert, Geib, Kolbe, & Brenner, 2003), and the primary purpose of customization marketing and CX is to make the customer feel unique. The use of BDA to better understand the feelings and mindset of the customers is essential to establish a trustworthy connection and gain engagement. Such analyses rely on formal surveys, call transcripts, comments on social networks, and any other type of exchange between a brand and a customer (Bleier, Harmeling, & Palmatier, 2019). Data analysts should analyze both quantitative and qualitative feedback from the customers in order to bring improvements to their product or service (Hassenzahl M., 2008). This helps marketers to adapt their marketing campaigns with customized content and communication plans to better reach and retain customers.

Big data technologies can also be used with the purpose of improving communication between a brand and its customers. It is extremely important in so far as ensuring good communication contributes to the reinforcement of relationships with the customers (Gebert H., et al., 2003). BDA can be configured to collect and analyze the customers' feedback and estimate satisfaction ratings (Bleier, Harmeling, & Palmatier, 2019). Analyzing such data will help identify the expectations of each customer and draw a context that enables more efficient and effective storytelling about a company or product. The company is able to exploit these data to improve communication with their customers and detect business opportunities on social media or directly on its website (Rose, Hair, & Clark, 2011). As a result, marketing professionals are able to improve and adapt their communication techniques to enhance the physical or online customer experience and thereby increase customer involvement.

All in all, the application of big data technologies to the customer experience improves communication and marketing performance. By evolving a thorough analysis of a business's communication channels, BDA can leverage valuable information to deliver richer customer experiences. By establishing such a connection between the brand and the customer, a company ensures the creation of a trustworthy relationship, thereby enhancing CX, customer loyalty, and sales.

3.3.2 How do big data technologies streamline customer service?

Successful customer service throughout the customer lifecycle can have a great impact on the customer experience. If CRM platforms are excellent media to provide optimized customer services after the purchase, big data technologies help to streamline customer service before and during the purchasing process. Merchant website operators have developed big data-based messaging systems to directly interact with their customers in order to enhance CX by providing relevant information or assistance (Smestad & Volden, 2019).

These big data-based message systems are called *chatbots,* and their implementation on websites, forums, and social media platforms has been increasing in recent years. The purpose of a chatbot is to understand and answer users' questions or demands by mimicking human intelligence. Thanks to powerful BDA, chatbots produce automated interactions between the customer and the company through a messaging interface (Rao, Akbar, & Mall, 2019). Although there are numerous limits to automated communication, chatbots are effective tools for assisting in the realization of basic tasks such as answering questions, orienting customers, proposing products or services, and proceeding to payment (Van den Broeck, Evert, & Poels, 2019). These big data-based robots are capable of interacting in real-time with customers and enable friction-free conversations with the brand. Finally, chatbots can also help companies reduce customer support costs and facilitate dialogue with customers, thereby improving the customer experience (Jeong & Kim, 2019). Insights from these conversations also enable brands to offer personalized recommendations to consumers.

All things considered, chatbots serve as an intermediary between brands and customers by understanding and meeting the latter's demands. Beyond their capacity to accompany customers and recommend products, these big data-based enhance the customer experience by facilitating conversations and meeting customer's needs as well as reducing company's customer support costs.

3.4 The stakes of artificial intelligence in marketing

3.4.1 AI-based analytics

Artificial Intelligence involves developing computer programs to complete tasks that would otherwise require human intelligence (Ziyad, 2019). In a marketing context, AI technologies generate customer descriptions, recommendations, customization, and predictions (Lexcellent, 2019). Data mining (DM) and machine learning (ML) technologies are the fundamentals of AI. In a marketing context, Stubbe and Coleman (2014) describe DM as a process that entails extracting commercially relevant information from a large mass of data in order to enhance marketing actions and descriptive models (Murdoch, Singh, Kumbier, Abbasi-Asl, & Yu, 2019). ML represents computational methods that entail learning from the customer experience to make predictions that help optimize product development, marketing campaigns, or recommendations (Akerkar, 2018; Rebala, Ravi, & Churiwala, 2019).

3.4.2 Descriptive models: learning from the past to improve future performance

One of the most relevant functions of AI marketing technologies is the development of *descriptive models*. Descriptive analyses are based on DM techniques that aim at translating raw customer data into valuable information and facilitating decision-making processes. As a point of principle, descriptive analytics describe and study historical information about a business's customer data, production, stock, marketing operations, sales, and financials. Such tools have become crucial in marketing because they enable a company to learn from its customers' past behaviors or needs as well as understand the impact of such data on future behaviors or needs.

Descriptive models are commonly used in marketing and sales to gain insights into previous actions and optimize the decision-making process for the management of future marketing or sales actions. The major innovation brought by AI technologies in the realization of descriptive models is the capacity to process larger customer datasets at a faster pace. AI-based descriptive analytics analyze data collected in real-time and provide live visualization supports such as dashboards or graphics to provide companies with instantaneous insights into customer knowledge and the results of their marketing actions, which enables them to quickly intervene to optimize marketing performance.

Finally, AI-based descriptive analytics can produce *automatically generated content*. Based on real-time analyses , descriptive analytics optimizes the visualization of information to enhance business intelligence. Descriptive analytics are commonly accessible in data visualization platforms such as Power BI from Microsoft. AI technologies have a great impact on marketing because they enable the establishment of descriptive models that analyze past marketing data in real-time in order to contribute to a more effective and adaptive strategy decision-making process. The results drawn from these analyses are instantly visualizable on BI-based supports.

3.4.3 Prediction models

Increased consumer mobility in the age of big data requires prediction and simulation, and the ability to predict demand and purchasing behaviors can bring a real competitive advantage in all lines of business (Del Vecchio, Secundo, Maruccia & Passiante, 2019). Predictive analytics are ML-based technologies that utilize propensity models to analyze customer data in order to predict future demand, purchasing patterns, or other customer behaviors (Giannelloni & Le Nagard, 2016). According to Thiraviyam (2018), by using predictive analytics, *"the target audience and the campaign objectives are defined, and the propensity model automatically recommends strategies to achieve the desired goals,"* which opens a wide range of business perspectives, including sales prediction, marketing project management optimization, and customer behavior prediction.

Predictive analytics can improve marketing performance throughout the entire customer lifecycle. Predictive marketing analytics are capable of determining upstream and downstream commercial opportunities with potential or existing customers, thereby enabling marketing managers to better apprehend the way customers buy (Burka, 2016). Based on collections of data about purchasing behavior or disruptive elements in the market, marketing professionals can manage their resources and efforts in a more efficient and cost-effective manner so that they can develop or adapt their strategies to better appeal to customers (Cappelli, 2019).

Thus, the use of predictive analytics for predicting demand and sales enhances marketing performance and sales productivity. Using machine learning technologies, analysts can identify elements of success or market disruptions based on purchasing patterns and other customer behaviors as well as external influences such weather or seasonality and use the results to predict sales volumes for a given period (McKinsey & Company, 2015). Recency-frequency-monetary (RFM) models enable the determination of sales projections for targeted customer segments and to identification of the most profitable or risky segments of the market, thereby informing decision-making for specific marketing operations or to withdraw from the market (Mardanov, 2016).

In short, AI-based predictive models have a strong impact on marketing performance because they provide analysts with the capability of making accurate predictions from the study of purchasing patterns, other customer behaviors, and external data. Predictive marketing analysis creates an ideal customer profile to represent the most loyal customers and is useful for identifying *lookalike* leads or customer segments that are most likely to buy as well as generating precise sales projections for specific market segments (Burka, 2016). Thus, marketers can adapt their strategies and avoid failure as well as increase efficiency and cost-effectiveness.

3.4.4 Business process automation

Business-to-consumer (B2C) and business-to business (B2B) professionals use predictive analytics in marketing and sales to automate and optimize processes for analyzing customer data, identifying leads, and extract valuable information (Burka, 2016). This process is called *business process automation* (BPA) or *marketing automation* (Little, 2001). These AI-based technologies systematically develop manual procedures for marketing- or business-related operations following specific rules and can execute a variety of features to improve marketing and sales efficiency (Watson & Holmes, 2009).

Customers tend to exhibit greater engagement in response to personalized marketing message (Dijkstra, 2008). In B2C contexts, BPA entails using AI-based analytics to deepen customer or client knowledge through DM and ML and customize marketing messages as well as trigger and run marketing operations and campaigns virtually without human intervention (Heimbach, Kostyra, & Hinz, 2014). In B2B marketing, the same combination of DM, ML, and BPA technologies is applied to reach customers and facilitate the processes of marketing and commercial prospection. Business automation optimizes sales professionals' productivity, decision-making processes and ROI as well as enhancing customer satisfaction and loyalty (Watson & Holmes, 2009).

3.4.5 How is AI applied in marketing automation to improve marketing actions?

AI and marketing automation technologies have emerged as key strategies in the field of digital marketing targeting B2C customers. Following initial configuration and development of the necessary technical infrastructures, automated marketing operations can be run without the intervention of data experts or marketers. E-mail is particularly suitable for automated marketing actions (Niccoli & Le Ouay, 2018), as each consumer action can generate an e-mail. Automated marketing can occur after buying a product, using a promotion code, or the cancellation of a basket on an e-commerce website (Mester, 2017). The process of optimizing automated e-mail frequency is based on the concept of *lead nurturing*, which consists of maintaining or reinforcing marketing relationships with customers (or leads) who are not yet ready for a sales action or in cases when a marketing strategy has failed. The objective of a marketing campaign is to enhance lead nurturing and thereby increase the ROI (Heimbach et al., 2014). Providing relevant information to the appropriate customer is the key to lead nurturing, and as indicated above, it is also critical to identify the optimal sending frequency for marketing campaign e-mails. ML technologies are able to automatically study the behavior and perceptions of a target customer when they receive a marketing e-mail, learn from the collected data, and determine the perfect sending frequency.

AI and marketing automation programs also have a positive impact on online marketing relaunching efforts, which aim to revive a customer's attention toward a brand's products or services of a brand, prompt the validation of an online basket, or alert them about special offers (Huret & Huet, 2012). Automated marketing operations entail the use of data-mining-based descriptive analysis to transmit the most relevant information for sending follow-up e-mails to offer cross-selling or targeted reduction offers to target particular customers. The sending frequency and process will be automated and optimized according to the target customer's behaviors or needs.

AI and marketing automation have a positive impact on marketing efficiency and cost-effectiveness because their use provides marketing actions and campaigns with a high level of precision and consistency. Machine learning optimizes sending frequency for marketing campaigns to adapt to customers' behavior and preferences and enhance their engagement with the brand. Finally, relaunching marketing campaigns are perfected with DM and provide the right content to the right person.

3.4.6 How are AI and business automation beneficial for commercial prospection?

In B2B contexts, marketing actions align with commercial prospection or market research, and methods are focused on the identification of prospects, collection of customer data, and prioritization of leads in order to optimize the realization of marketing actions and the probability of closing a deal. The success of marketing actions in the B2B sector depends on upstream research (Watson & Holmes, 2009), and marketing and sales professionals use AI and BPA technologies to identify and study potential new customers. AI and BPA facilitate *prospect discovery*, which is the process of using *ideal customer profiles* to find net-new prospects to add to the marketing database (Burka, 2016). Burka's (2016) research demonstrates that predictive marketing analytics can be applied to internal B2B customer data warehouses with the aim of identifying behaviors and needs that will help build purchasing predictions and building a list of new prospects or long-term customers who have not purchased particular goods or services. Businesses can also use external data to collect information about the market to complete their analysis.

Another field in which AI and BPA have an impact is *lead enrichment*, which is the process of filling in data gaps to provide insights into a lead's needs, interests, and intentions. Enrichment blends clients' data with third-party data and can add unstructured information culled from the open and social web (Burka, 2016). Descriptive analytics platforms are indispensable in this process because the AI technologies are able to transform unstructured data from the Internet into structured databases. Using matching algorithms, marketers are capable of establishing precise customer profiles and deepening their customer knowledge. Lead enrichment plays a great role in *lead scoring*, which entails assigning a value to each lead based on a predetermined set of rules or criteria (Burka, 2016). Predictive lead scoring models integrate the data collected during the lead enrichment process and calculate scores for each prospect (or lead) to evaluate his/her likelihood of answering positively or purchasing (Kotler, 2018). These scores help marketing managers to prioritize their leads and optimize their marketing messages.

In short, prospect discovery enables B2B companies to identify the persons of their prospects and establishes a lead set from which to choose, following which lead enrichment and scoring collect customer data to deepen customer knowledge and better prioritize leads. AI and BPA technologies enhance productivity by concentrating resources on the leads that have been foreseen to be most profitable. BPA technologies create automated messages that will enhance customer engagement and increase the ROI of the marketing campaign.

4. Research methods

The main purpose of this study was to identify ways that BDA can be used to understand and enhance a firm's marketing performance. For this purpose, we used a qualitative method based on semi-structured interviews and then employed an inductive approach to identify emerging themes and classes (Binder &Edwards, 2010; Braun & Clarke, 2006; Fereday & Muir-Cochrane, 2006). As proposed by Barratt, Choi, & Li (2011) and Wilhelm, Blome, Bhakoo, & Paulraj (2016), the target population comprised individuals holding top positions in various companies across different industries in India (Table 1). These executives are vigorously connected to company decision making process and thus are sufficiently knowledgeable to provide useful insights about company and industry level concerns on the topic of the impact of BDA on firms' marketing performance. The semi-structured interview procedure is included as Appendix. Participants' identities have been obscured to maintain anonymity. Notably, saturation was reached after 10 interviews.

The collected data was first coded to highlight repeating patterns and themes, and associations between different themes were identified to determine relevant categories (Braun & Clarke, 2006; Meredith, 1998). Data was triangulated between a literature review, respondents from different companies, and archived reports and other primary documents to counter researcher biases and ensure validity and reliability (Eisenhardt, 1989; Pagell & Wu, 2009; Voss et al., 2002).

Table 1. Characteristics of interview respondents

Respondent	Position	Industry	Company size (employees)	Total work experience	Education
R1	Manager/Sr. Manager	Food and Beverage	500–1000	5–10 years	Post-graduate
R2	Head of Business Development	Manufacturing	> 1000	> 10 years	Post-graduate
R3	Co-founder and Head of Insight	Advertising and public relations	> 1000	3–5 years	Graduate
R4	Director/CEO/Founder	Manufacturing	> 1000	> 10 years	Post-graduate
R5	Consultant	Construction/ Real Estate/ Infrastructure	> 1000	3–5 years	Graduate
R6	Head of Marketing	Travel and Tourism	500–1000	> 10 years	Post-graduate
R7	Chief Marketing Officer	Food and Beverage	> 1000	> 10 years	Post-graduate
R8	Manager/Sr. Manager	Professional and technology services	500–1000	3–5 years	Graduate
R9	Head of Marketing	IT	> 1000	> 10 years	Post-

		Services/Software			graduate
R10	General Manager	Food and Beverage	500–1000	5–10 years	Post-graduate

5. Findings and discussion

The major themes and sub-themes gleaned from the research are elucidated in the sub-sections below. Tables 2 and Table 3 present the various themes and sub-themes along with exemplary interview excerpts.

Table 2. Initial codes

Excerpts	**Initial codes**
What's available has enhanced, and the number of sources has enhanced, and that needs a more sophisticated set of skills to species and prioritize. (R2)	Cognitive deficit
It may gather correct and big data from numerous practices and inputs in process in short period with real time information that may assist decision makers. (R8)	Cognitive computing: capacity to hold huge datasets and real-time decision-making support
…you don't know whether you're speaking with a group of persons who really have their finger on the rhythm of what's driving their company, or whether they're in [a state of] 'self-delusion'. (R1)	Cognitive bias
Personally, I feel that one of the weaknesses of cognitive computing tools will be the capacity to comprehend trust associations between the business and the clients. (R5)	Insufficient consideration of client trust and bond issues
I don't believe you've got sufficient hours in a day to find solutions for these problems. (R2)	Cognitive burden
There is too much big data to analyze efficiently. In addition, I have a doubt that the boards continually and actually get to engage with big data. (R6)	Data handling competency
A smart cognitive computing system will be proficient to combine the information databases and knowledge from everywhere, and with that, the system will be competent to present decisions more evidently and usefully, besides being capable of covering broad knowledge that the businesses single-handedly lack adequate data about. (R4)	Broad range of data inputs
They start worrying at that point, as any business change that's essential for them to catch that completed is vast, (R7)	Decision process distraction
No incorporation of technology, no incorporation of databases, but a lot of affluent full-grown staff [on the board],	Board composition and competencies

adhere onto their incredibly key jobs for valued life. (R9)	
Big data is rising much quicker than the capacity to analyze it. (R3)	
I don't see anyone holistically altering their complete business due to data. (R4)	Data concerns
I'm not confident how having this vast data collection will make it significantly easier to make a number of these big strategic decisions. (R6)	Input for strategic decisions
When it comes to the board … they completely depend on us [outside big data source]. (R10)	Other stakeholders
They're concerned about … giving away intellectual property. (R9)	Organizational impacts of sub-group formation

Table 3. Generation of final themes

Sub-themes	**Category**
• Cognitive deficits • Capacity to hold huge datasets and real-time data support for decision-making • Cognitive bias • System's lack of consideration for client trust and bond issues • Cognitive burden	Cognitive characteristics
• Data-handling competency • Broad range of data inputs • Decision process distractions • Board composition issues • Input for strategic decisions	Board cohesion
• Temporal concerns	Time constraints
• Other stakeholders • Organizational impacts of sub-group formation	Accountability and control

5.1. Cognitive capabilities

As a knowledge-based resource, big data is expected to generate dynamic and adaptive capabilities that can assist in strategic decision-making processes. The results indicate that the efficiency of such processes depends on the competent combination of big data resources (i.e., the data itself) and capabilities (technological capacity to capture and control data). The majority of informants identified the contribution of big data in this process. As one manager mentioned, 'They have all obtained the insights they have on particular issues and they know that gathering great amount of data may permit them to split a few of those issues; thus they have all acquired to that initial base' (R8).

The majority of respondents reported difficulties incorporating big data resources and developing the required capabilities, which signifies that some companies lack the capacity to accumulate, handle, and analyze big data. Many participants' companies lacked awareness of the benefits of using big data to improve decision-making, and a few businesses 'may feel themselves in dilemma with a number of stakeholders' (R3). Indeed, as Helfat and Petraf (2015) found, the cognitive capabilities that support these dynamic and adaptive capabilities emerged as a vital theme. Several managers and directors highlighted the cognitive demands that big data imposed on board members. Moreover, as one director clarified, additional time is required to identify the patterns revealed by big data, 'There is also knowledge concerning the "learning curve" that companies have to go from beginning to end... even I have to go from beginning to end… and my team as well' (R7).

This study recognized five sub-themes related to cognitive characteristics that can affect strategic decision-making: cognitive deficits; insufficient capacity to hold huge data-sets and provide real-time decision-making support; cognitive biases; systems' lack of consideration of client trust and bond issues; and cognitive burden. The connections between these sub-themes relate to the limited 'ability of individual managers to execute intellectual actions' (Helfat & Peteraf, 2015, p. 832), which can result in cognitive bias (Brennan, 2016), a condition that is frequently experienced by those besieged with extensive amounts of data. Gupta et al. (2018) argued that big data analytics and cognitive computing are augmenting data analysis. Hurwitz et al. (2015) found that professionals who mainly work with analytics and big data will see how "cognitive computing" builds on their foundation, and facilitates more opportunities.

5.1.1 Cognitive deficits

The results indicate that many participants' companies lacked the technical capacity to combine, construct, and rearrange essential inner and outer competencies to make use of big data, although the fundamental principles of employing data to update decision-making did not significantly vary. Although respondents acknowledged the potential of big data to enhance marketing strategy, they generally considered themselves to be badly equipped to handle it, as, 'being competent to extract and find the insights […] is a technological action that calls for intense responsibility analytics' (R8). Participants expressed unease with technological developments and digitalization, which several perceived as being the purview of younger generations. Indeed, in line with this, Merendino et al. (2018) found that there is a deficit in directors' capabilities for dealing with analytics and Big Data.

5.1.2 Capacity to handle large datasets and real-time decision-making support

Most respondents perceived that cognitive systems based on logical and knowledge capabilities could help them attain more comprehensive insights derived from a range of data. As one founder suggested, 'having a strategic business with a corporation that has cognitive computing-based knowledge may actually be useful […] fresh insights exposed by cognitive skills may be greatly valuable to look at latest and dissimilar corporate opportunities' (R3). Similarly, one manager expressed the view that 'cognitive computing may look at different forms, which we may not recognize via examining the data. Thus, this technology can make sure that the boards' strategic decisions are well-informed'(R8). Finally, R5 mentioned that 'an elegant cognitive computing system will be competent to combine information databases and understandings from everyone in the company. Such a system will be capable of presenting decisions much evidently and more usefully, besides being proficient to cover broad comprehension areas where individual businesses lack adequate data. Indeed, Merendino et al. (2018) established that strategic decision makers need to develop cognitive capabilities and explore latest ways to make successful decisions in Big Data era. Argote & Miron-Spektor (2011) presented a framework, where organizational experience interacts with the context to facilitate knowledge.

5.1.3 Cognitive bias

Some participants indicated that traditional marketing approaches hampered decision-making practices because many managers were suspicious of big data. As one business manager confessed, 'there is constantly the doubt about the use of information and data […] and I appreciate there is an aspect of carefulness' (R1). Participants expressed a concern that data could be misinterpreted such that companies may utilize big data '…as a result of this channel consequence because you set off towards the highest point […] I'm not confident that the boards are always actually catching hold of big data (R9).

Indeed, Phillips-Wren et al. (2019) investigates about why cognitive bias matters in the context of data driven decision making, consider 'cognitive bias' and big data. This Big data may present an immense amount of latest data, so both as to recency and size it has tendency to deluge small datasets and may be more important data, which might be relevant in a particular decision-making context. Conditions seem set for cognitive bias to edge into decision making as big data becomes more popular. Similarly, Crawford (2013) explored the hidden biases in big data and analytics and believed that cognitive bias is one of them, which must be considered during strategic decision making.

5.1.4 Insufficient consideration of client trust and bond issues

Cognitive computing technologies facilitate analytical capabilities and enable the consideration of numerous potential options. However, although computing systems may support data compilation and analysis, the ultimate decision is made by the board, which is also informed by personal opinions and other insights (Fahimnia, 2018). Cognitive systems may consist of various unstructured data for analysis; however, some respondents believed that their use could override human factors such as client relationships. As R5 expressed, 'personally what I feel, one of the weaknesses of cognitive computing tools will be the capacity to comprehend trust associations between the business and the clients."

5.1.5 Cognitive burden

A cognitive burden arises when individuals are exposed to more information than they can competently process (Merendino et al., 2018). According to R6, 'businesses still have an excess of data […] and occasionally a smaller amount of data is superior than extra data'. Respondents perceived difficulties analyzing large datasets to complicate strategic business decision-making. For example, although R5 noted the 'closeness … and … interrelatedness' of data patterns, he also suggested that companies could encounter too much 'big data to truly be proficient to analyze successfully'. However, a chief marketing officer expressed the view that big data enabled analysts to 'formulate decisions derived from reality' (R4).

Indeed, Loebbecke and Picot (2015) provided the mechanisms underlying how big data analytics and digitization drive the revolution of companies and society and highlights the possible effects of big data, analytics and digitization in the context of cognitive tasks.

5.2 Board cohesion

This theme encompasses issues regarding boards' competency to handle big data, concerns regarding the broad range of data inputs, distractions in the decision process, board composition and the ability to employ knowledge gleaned from large datasets to make strategic decisions.

5.2.1 Broad range of data inputs

Some participants indicated that big data may not necessarily always yield high quality insights. Even those who expressed confidence regarding big data insights remained cautious that although digital tools have transformed or improved the quantity of accessible data, 'the decision-making practice is much based […], on improved quality information, much vigorous information, that may obscure what's really going on' (R1). Similarly, R6 cite the risk that excess data could hinder marketers' ability 'to truly be competent to analyze [it] successfully'. Indeed, Merendino et al. (2018) examined that board cohesion can be impeded via Big Data, compromising the decision-making process.

5.2.2 Data-handling competency

Participants expressed concerns about boards' ability to handle big data, as they are under pressure 'to transform their firms as speedily' as possible (R4). As R7 explained, companies are 'a time of transformation, a time when the entire marketplace is shifting how it purchases and feels about objects'. Thus, meeting the requirement for big data to serve as a fundamental tool for company operations while managing boards' competency was a substantial concern: 'customers may not suspend their organizations …we believe there's a flash in time, when somebody thinks "I have search it out. I can transform my business and all is settling to be alright." Nevertheless, they require putting on the market a bit by means of the presented system and existing company with boards' competency as well (R 2).

Indeed, Merendino et al. (2018) established that boards need to have cognitive capabilities and handle the data via exploring novel ways to decision making in the age of Big Data .

5.2.3 Decision process distractions

Respondents also expressed the view that inconsistencies in big data could distract from the strategic decision-making process, which fueled concerns regarding boards' analysis capabilities and the resulting negative impacts on the company: 'We regularly encounter circumstances when there are large differences in data, as evaluating objects is confused— it's actually hard at times.

Even with an effortless set-up, objects are repeatedly set out slightly incorrectly, and you might be making bad decisions' (R9). As R7 emphasized, boards tend to be comprised of middle-aged men who generally lack technical know-how or familiarity with large databases and often resisted new technologies. Similarly, R7 explained that 'conventional marketing is […] somewhat fixed in the inheritance area where you notice […] numerous old-style Marketing Directors [who are] actually fighting with the innovative digital world'.

Indeed, Wamba et al. (2015) established an interpretive framework, which examines the applications of 'big data'. They also examine the strategic and operational impacts of 'big data' on firm performance.

5.2.4 Board composition

The majority of respondents considered big data technologies as being more easily handled by younger adults, whereas many 'board members [are] in the 40s or 50s' (R5), and a number of companies continue to operate according to '1980s principles' (R2). Participants expressed the need for boards to demonstrate accountability through conservatism, and some suggested that using big data would not yield major profit increases: 'boards have to remain considerate of their company, their marketplace, and the decisions they must take […], ultimately, all big data provides them is a small move, if you like, from 30%, to 40% or 50% [...] they will not go past 60%' (R4). As one executive explained, big data could not supersede human knowledge and strategy: 'I am not confident how having this vast data bank and information will help make large decisions easier; you still need to carry your individual intellect, reasoning, your individual vision in light of decisions' (R1).

5.2.5 Input for strategic decisions

Participants generally acknowledged the usefulness of BDA for exposing strategic possibilities by investigating external technical and market-related data in conjunction with internal competencies and activities. As R3 explained, 'it speed ups, improves human proficiency. It may develop more insights with personnel, link spaces between insights and improvements. It may better identify with persons. It may develop contacts and solutions for company problems'. A senior manager noted that 'there is countless data that is created in my business, and we are not proficient to manage and interpreting this data. Big data tools may contribute every type of data, [and] as a result, my business may probably identify the latest possible dealing opportunities'. Similarly, R1 stated that, 'these big data tools may assist in combining dissimilar data forms in preparation practice and permit the system to see and analyze the connections in the data at quicker speed. It reduces human errors. It exposes numerous pioneering opportunities across companies for strategic decisions'. Indeed, Intezari and Gressel (2017), described a theoretical framework on the use of knowledge management system and revealed how this system can permit the inclusion of big data in strategic decision making. For the same four types of data oriented decisions and a set of basic principles are recognized toward facilitating knowledge management system to manage advanced analytics and big data.

5.3 Time constraints

This theme was categorized into sub-themes encompassing temporal constraints and other timing issues. Respondents highlighted the speed of big data hope BDA enables to faster analyses: '…we have completed corporate projects in five to six weeks, back-to-back—so go into, search out the data, place it into a platform, cooperate with analytics, divide the database, and after that make some models' (R10).

Other participants cited the advantage of obtaining early insights. However, the speed of big data did not always translate into the capacity for rapid action, as big data was observed as 'rising more rapidly than the capacity to analyze it' (R6), and '…the market may not work on that timeline' (R9). Companies address these issues by means of different short- and long-term fixes. For instance, in short term, respondents highlighted the need to be practical regarding what big data might reveal and consider it as a supplement rather than a replacement for established practices: '…digital will add to this face-to-face real time experiences' (R3). Respondents also discussed using social media-based insights to make smaller changes to their customer targeting approaches.

5.4 Accountability and control

5.4.1 Other stakeholders

Some respondents indicated that facilitating customer support mainly depended on outsourcing connections. In such cases, boards tend to cede control over marketing strategies. As R9, an IT services marketer, explained, 'the board […] they entirely trust in us [external big data supplier]!' Similarly, one director claimed that 'we have scored some initiatives from other distributors that were performing original things.' However, R7 expressed the concern that 'many board members are very much dependent on consultancy suggestions and are most likely receiving information cast-off. You may not mainly charge the board executives with that [responsibility], as it's not their specialty, and that adds to danger […] And sometimes it does hit me that the persons in succession with the company are […] not always competent to hold some of these things'. In this regard, our study reveals the contribution of a wide range of stakeholders in determining how big data is converted into knowledge and action. Indeed, Gupta et al. (2019) outlined that relationships management among stakeholders is a vital factor when we make use of big data and analytics. Similarly, Someh et al. (2019) highlighted based on discourse ethics and stakeholder theory the diverse ways to balance interactions among persons, firms, and society to encourage the ethical use of big data and analytics.

5.4.2 The organizational impact of sub-group formation

Whereas respondents did not recommend that boards should transform the structure of whole organizations to handle big data, several called for establishing new leadership roles for BDA specialists, such as 'Chief Science Officers', 'Chief Data Science Officers', or 'Chief Analytical Officers'. In reality, only a small number of corporations are appointing authorities to build up new skills and develop innovative big data infrastructures. In general, these new hires occupy senior roles in big data teams that shore up board decision-making. R10 explained that 'the expertise [concerned in dealing out big data] decides what is potential, and thus, the inspiration [lies] inside the checks of tools in a manner that was less so in the past'. Thus, this type of effect is having most important impact on how the board performs and reacts to the incorporation of information obtained during the analysis of big data.

Thus overall, the results of present paper agree with the extant literature; however, a few findings diverse from those mentioned in previous works. This might be due to the difference in i) economy and sector, ii) technical, non-technical, internal and external factors concerning the use of big data and analytics, and iii) methodology used in prior works, whereas, the results will assist decision makers to know relevant factors for the implementation of big data and analytics for firm pperformance, specifically from marketing perspective. Further the conceptual model proposed based on the themes and sub themes emerged from thematic analysis in this study is shown in Figure 1.

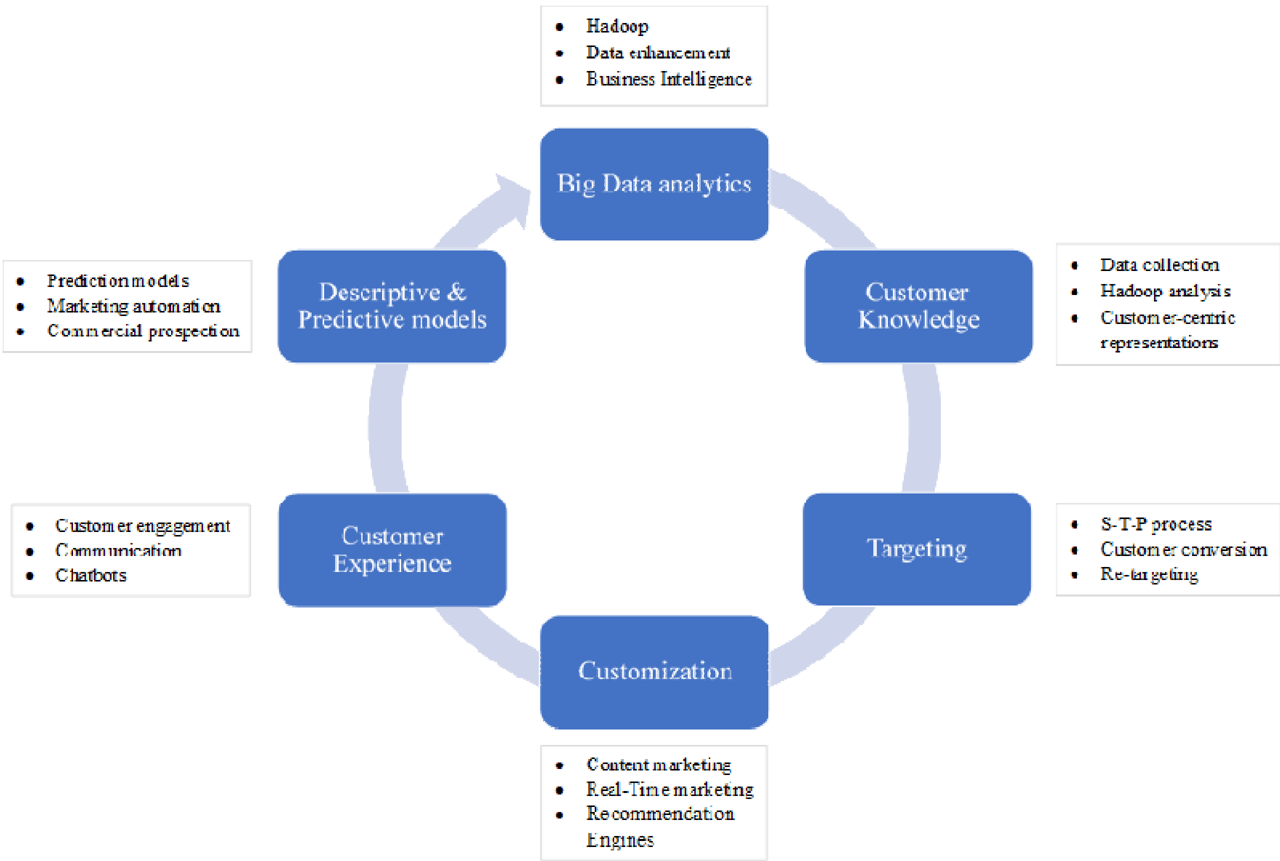

Figure 1. Proposed theoretical model on marketing performance using BDA

6. Discussion

Big data has emerged as one of the main domains of corporate technology and is attracting interest from numerous industries for its ability to leverage the transition towards Sustainable Development. To keep pace with the data revolution, firms must make adjustments in company structure, client dealings, and business models. How businesses can achieve a competitive advantage by deploying big data driven practices requires detailed study and extensive research.

The present study examined the potential roles that big data can play in enhancing firms' marketing performance. The findings highlight how the integration of knowledge and information assists operational and strategic decision-making. Particularly, in this study a Big Data based Knowledge Management model is proposed, which outlines the centrality of knowledge as guiding principle in the use of big data and formulate marketing strategy in organizations. It is recommended that scholars and practitioners in the area of knowledge management must be able to control the application of big data, and calls for future study examining how knowledge management can theoretically and operationally use and incorporate big data to cultivate managerial knowledge for superior decision-making and organization value creation. The proposed model is one of the early models putting knowledge as main consideration in the effective use of big data in organization and frame marketing strategy. As such, this paper presents valuable insights for scholars and practitioners interested in better understanding the interplay between big data analytics and marketing strategy.

6.1. Implications for research

This paper has a number of theoretical implications for Industry 4.0, specifically the research in the domain of Big Data. Firstly, it is among the pioneering work to study about big data and firm marketing performance through the lens of knowledge based view. Though there is enormous literature on big data (Kim et al., 2012) and firm performance (Wamba et al., 2016), studies on incorporation of the two constructs in single work is limited. The role of big data analytics on firm performance emerges evidently from the past literature. What is not as much understood is the role of big data analytics specifically to influence the firm's marketing performance. Therefore, present work assessed the role of big data analytics in shaping firm's marketing performance using data collected via qualitative methods from Indian firms. The present paper also put together the concepts of big data, knowledge based view and firm marketing performance in a single model and brings together what had earlier been supposed to be independent constructs. Previously, the joined effects of big data analytics and firm marketing performance have rarely been examined. Finally, via considering the approach of knowledge based view, this paper reveals that this view assist to understand the connection between big data and firm marketing performance in an effective way.

Despite a lot of subjective argues about the enabling effect, which big data have on increasing existing or apprehending performance gains, there is dearth of empirical studies to consolidate them. The results of current study reveal that diverse combinations of resources related to big data have a larger or smaller importance depending on context specific. Particularly, this study finds that cognitive capabilities, board cohesion, board composition, time constraints, accountability, control towards stakeholders and sub-group formation resources contribute towards marketing performance gains, whereas organizational cognitive characteristics and managerial skills are of larger significance. Indeed, there are a number of business reports which talk about the relevance which managerial characteristics may have in comprehending business

value (Kiron, 2017), but only a few empirical support to prove such argues and reveal what sets of aspects make possible the performance gains. The findings of current study reveal that big data should not be considered as an only technological challenge, but to a certain extent, an organizational one that involves blend with the organization business strategy. Thus, considering the important constituents, which facilitate such a blend between big data and corporate strategy, and that consequently initiate the performance increases, is vitally essential.
The results of this study suggests that the strategies surrounding big data are formed and implemented depending on some aspects, For instance cognitive capabilities, board cohesion (with broad range of data inputs, data-handling competency, decision process distractions), board composition with input for strategic decisions, time constraints and accountability with some control towards stakeholders and sub-groups. Additionally, this study also indicate some other sides that are about to appear as key competitive differentiators in coming time, for instance the Data-handling competency issues contiguous with the use of big data and the trust build up between organization and their clients.

6.2. Implications for practice

The key results of this paper provide assistance to consultants and managers who are directly involved in executing big data analytics in firms. The insights derived from knowledge based view undoubtedly emphasizes on how, in hesitant situations, use of big data analytics can be leveraged as a key source of firm sustainable competitive advantage. On the other hand, if knowledge based view is misplaced, then big data analytics that can be useful in the current state, may be unable to have competitive advantage, provided that the firm situation is extremely dynamic in nature. The result that big data analytics robustly affect firms' marketing performance point out that, to turn big data analytics into firm marketing performance, managers should focus on proper and timely use of big data in their organization. Likewise, managers may look at the board cohesion so as to have broad range of data inputs, data-handling competency, decision process distractions and input for strategic decisions and many more. This assists to make sure about effective use and management of big data, which is one of the mainstays of firm marketing performance. Another important theme emerge from this study findings is managers consideration towards cognitive capabilities so as to overcome cognitive deficits, cognitive burden cognitive bias, insufficient consideration of client trust and bond issues on time. It will also provide capacity to hold huge datasets and real-time decision-making support to the managers and consultants.

6.3. Limitations and future research

The proposed model in this study is robust and firmly grounded in theory and author(s) have assessed it via gathering qualitative data from Indian firms. However, a few limitations and unreciprocated questions need be tackled. First, the present study is conducted within a particular area of big data and in one context. Though big data and its related analytics via its nature is context specific because of the differences in analytics industry, reproductions of our proposed conceptual model in other situations could improve its generalizability. Next, this paper used qualitative method to collect data; therefore it is further suggested to retest the results with panel data to examine its constancy. Further, in this paper we generate a few themes based on data collected via structured interviews from Indian firms, future work could be replaced via incorporating empirical measures of big data analytics and its influence on firm marketing performance, so as to present an actual picture. Next, it is also suggested developing context specific big data analytics instrument such as supply chain analytics, customer analytics etc via thorough scale validation process to better measure big data analytics for different sectors or industries. Lastly, it is recommended examining the influence of organizational factors such as organization culture and commitment of top management regarding the execution of big data analytics capability in a firm, should be considered as mediating or moderating variables to further enhance understanding in the big data domain.

Conclusion

The main purpose of this paper was to fill an important gap in the existing literature concerning the role of big data in enhancing firm marketing performance. For the same, a conceptual framework was presented with essential elements that are required for marketing performance using big data and analytics. The study made use of qualitative analysis and presented the findings through the lens of knowledge-based view. In addition, based on semi-structured interviews a number of themes and sub themes were generated using thematic analysis that further leads to the identification of a number of emergent categories. Our results reveal interesting findings that cognitive capabilities, board cohesion, board composition, time constraints, accountability, control towards stakeholders and sub-group formation resources contribute towards marketing performance gains, whereas organizational cognitive characteristics and managerial skills are of larger significance. The findings also emphasize on significant gaps in conventional decision-making systems and reveal how big data improves firms' strategic and operational decisions as well as assists informational access for improved marketing performance. These key findings assist managers to appropriately allocate resources.

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Appendix: Semi-structured interview schedule

1. How do you employ data for daily operations in your company?
2. What are your views regarding using a BDA approach to deal with complex datasets?
3. How can BDA support a company's daily functions and decision-making?
4. How can BDA affect your business?
5. How can BDA affect your industry overall?
6. How can BDA affect your stakeholders in general?
7. In your view, what are the various issues that a company may face when applying a BDA approach for its dealings? (e.g., company actions, profits, stakeholders etc.).
8. Do you believe that big data can contribute to simpler means of controlling data in your organization? Why or Why not?
9. What type of company data would be more relevant for developing marketing strategies?
10. What are some company decision areas that may benefit from the use of BDA?