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Technology in the 21st century: New challenges and opportunities

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ABSTRACT

Although big data, big data analytics (BDA) and business intelligence have attracted growing attention of both academics and practitioners, a lack of clarity persists about how BDA has been applied in business and management domains. In reflecting on Professor Ayre's contributions, we want to extend his ideas on technological change by incorporating the discourses around big data, BDA and business intelligence. With this in mind, we integrate the burgeoning but disjointed streams of research on big data, BDA and business intelligence to develop unified frameworks. Our review takes on both technical and managerial perspectives to explore the complex nature of big data, techniques in big data analytics and utilisation of big data in business and management community. The advanced analytics techniques appear pivotal in bridging big data and business intelligence. The study of advanced analytics techniques and their applications in big data analytics led to identification of promising avenues for future research.

1. Introduction

In the last two decades, technological breakthroughs have ushered in a new era for businesses and governments (Amankwah-Amoah, 2017; Ayres and Williams, 2004; You et al., 2018). As Ayres and Williams (2004, p. 316) observed, "much of the world is connected via sophisticated networks that allow volumes of text, images, sound, and video to be exchanged in an instant". The field of business analytics has been one of the rapid growing and promising areas of business intelligence (Chen et al., 2012; Sheng et al., 2017). Business intelligence means the "concepts and methods to improve business decision making by using fact-based support systems" (Lim et al., 2013, p. 17). In this process, business analytics is concerned with methods and techniques for dealing with data to assess the past or real-time business performance, and it plays a critical role in the interconnected world (Davenport, 2006). Indeed, past studies have demonstrated that improvement in decision-making depends on progress in analytical tools (Ayres, 1984, 1989). This provides a solid basis for future business planning and decision-making by offering data users better knowledge and insights into business activities.

Technological progress is critical to the global economy (Ayres, 1988; Ayres and Williams, 2004), especially with new applications of information and communications technologies (ICTs) (Ayres and Williams, 2004). In the age of the Internet of Things, the exponential growth of technologies has brought greater complexity to business analytics (Beath et al., 2012). With significant scale escalation and scope expansion, the tremendous explosion of information has been called "big data", which is not only characterised by extremely large volume, but also by significance in its variety, velocity, veracity, variability and value (Gandomi and Haider, 2015; Jin et al., 2015; Katal et al., 2013).

Technological advancement and transition into a data-driven culture are important drivers for economic growth in the digital era; however, the prospect depends on the application of ICTs (Ayres and Williams, 2004). A growing body of literature supports the view that data-driven approaches, business intelligence and analytics largely depend on all kinds of data collection, information extraction and analytics techniques (Turban et al., 2008; Watson and Wixom, 2007). Although research on applications of big data analytics (BDA) and technological development have grown exponentially in the last 10 years or so (Ayres and Williams, 2004; Russom, 2011), there remains inadequate clarity about what advanced techniques have been developed given the challenges inherent in big data's nature and how BDA has been applied in the business domain and discussed in scholarly work.

Against this backdrop, the main purpose of this paper is to extend Professor Ayres' idea of the significance of technology in stimulating economic growth by recognising the importance of harnessing big data in the 21st century. We do so by surveying the literature on big data and BDA techniques in management application and outline directions for future research. This study is closely related to those of Chen et al. (2012) and Chen et al. (2014). One of our key arguments is that

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harnessing new technology and data to make better and informed decision can contribute to the wider discussion on different mechanisms for technological changes and driving economic growth and development.

Following the idea of big data value chain in Chen et al. (2014) and taxonomy of emerging analytics areas in Chen et al. (2012), we take on both technical and managerial perspectives to explore current research in the management community. We develop a conceptual framework illustrating that BDA is the key that bridges the gap between big data and business intelligence. To that end, we identify the key technological advancements that address big data challenges and depict how BDA has been discussed and applied in management research. By incorporating and clarifying big data, BDA and business intelligence, this study helps identify research and business opportunities. Although some studies have charted the historical evolution of big data (see Phillips, 2017), we steer away from such analysis to offer a more robust review of the current state of knowledge.

The rest of this paper is organized as follows. The next two sections clarify the key terms, scope and road map for this review. We then describe the findings on advanced technological enablers in BDA workflow and on BDA methods adopted in management applications. The final section presents the discussion and conclusion, highlighting the research gap and setting an agenda for future research on applying BDA in management.

2. Technology and big data in the 21st century

The term "big data" refers to the extremely large amount of structured, semi-structured, and unstructured data continuously generated from diversified sources, which inundates business operations in real time and impacts decision-making through mining knowledge from massive data (Phillips, 2017; Wamba et al., 2017). It presents a great opportunity to enhance our capabilities to better understand the world (Amankwah-Amoah, 2015, 2016). In addition, challenges inherent to big data are emerging that require technological advancement to help capture value from big data.

The proliferation of big data has inspired practitioners and academics to take advantage of it with more effective analytics (Phillips, 2017; Wamba et al., 2017). A host of factors such as diversified data sources and types, faster data generation speed and an urgent need of efficient analytics in such a data-driven business environment has motivated the advance in techniques to achieve better analytics performance. Indeed, technological breakthroughs and innovation have led to methodological improvements to perform complex data analysis over the past few years (Davenport et al., 2012; McAfee et al., 2012).

Advanced analytics, also known as discovery analytics or exploratory analytics, is a collection of techniques used to "discover new business facts that no one in the enterprise knew before" (Russom, 2012, p. 2). Applying advanced techniques to analysing complicated data sets has led to BDA (LaValle et al., 2011), which is comprised of advanced analytics techniques, hardware and software, platforms and tools to perform big data management and analysis. BDA is a combination of massive data sets and advanced analytics that investigates the specifically detailed aspects of business activities and provides on-going positions of the business (Russom, 2011; Wang et al., 2018). It provides great support for making decisions and taking actions based on evidence (Wang et al., 2018).

3. Conducting the review

As illustrated in Paré et al. (2015), a scoping review "attempts to provide an initial indication of the potential size and nature of the available literature on a particular topic" to "examine the extent, range and nature of research activities, determine the value of undertaking a full systematic review, or identify research gaps in the extant literature" (p. 186). This study is a mapping review that aims to clarify BDA research trends and identify the advanced techniques applied in current business intelligence. For this purpose, we adopted the best practice advocated by past studies (e.g., Cropanzano, 2009; Short, 2009; Webster and Watson, 2002) and employed by review studies such as Short et al. (2009) and Ucbasaran et al. (2013). We also followed the four-step process of doing content analysis as introduced in Seuring and Gold (2012).

The surveyed literature was comprised of English-written peer-reviewed papers on big-data-related topics covering a 16-year period from 2000 to 2015. We set up the review from the turn of this century, when big-data-related concepts started to gain prominence, although big data as a management-related term first gathered steam around the year of 2007 (Halevi and Moed, 2012). Given that research has flourished in both top-tier and lower-ranked journals, we decided not to limit the scope of the review to the status of journals in line with past reviews. In addition to articles published in academic journals, several conference proceedings, unpublished studies and book chapters were included.

To identify studies that describe techniques and their applications in BDA, extensive research in library services and major databases (including Informs, Business Source Complete, Sage, Wiley, Springer, Emerald, ScienceDirect, JSTOR, Other publishers' online service) was carried out. Structured keywords such as "big data", "big data analytics", "advanced analytics", and relevant terms of technologies and techniques were used to search and identify related studies. Depending on the sufficiency of search outcomes, combinations of keywords were used to extend or narrow selection results. In addition, to ensure the identified studies were within the scope of this review, a quick content check was conducted by reading the abstracts and considering the appropriateness of the topic based on the definitions in the previous section.

The next stage of the process entails a detailed examination of the whole paper and classification of selected papers according to the techniques applied in the study. Within the classification scheme, all papers are tagged with labels like the year of publication, authors, research methodology, key areas, key features and key findings. In all, 280 studies were identified and analysed in this study. Around 83% of the sample was from academic journals in management domains, while the remaining were conference papers, books or industrial research reports. Among the journal articles, most were in fields such as information management, marketing and operations, while there are fewer organizational studies, sector studies and general management subjects. Although it shows an imbalance in the distribution of subjects in the collected papers, studies into big data show a growing trend over the sample period, especially after 2010.

To delineate the findings, we utilised Fig. 1 as a road map that links big data, BDA and business intelligence as cores in a single framework. Fig. 1 shows the features and linkages between the various constructs, i.e., big data, BDA and business intelligence. At the first stage of this review, we focused on the technical aspect of BDA. We argued that the nature of big data presents technical challenges to data management and data analytics, but by applying advanced technologies and techniques at each stage of the analytics workflow, big data are manageable and valuable information can be potentially extracted to inform business decisions. Then we moved on to examine the application of advanced techniques in BDA for achieving business intelligence. Based on data types, we classified big data into structured data and unstructured data, which corresponds to the classification of emerging BDA areas described in Chen et al. (2012). The focus at this stage was to look into the application of analytics techniques in management research.

4. Technology in big data analytics workflow

Due to the challenges of big data in terms of huge volume, high variety, high velocity, high variability, low veracity and high value, greater efficiency is a primary goal in handling such data sets. Ayres

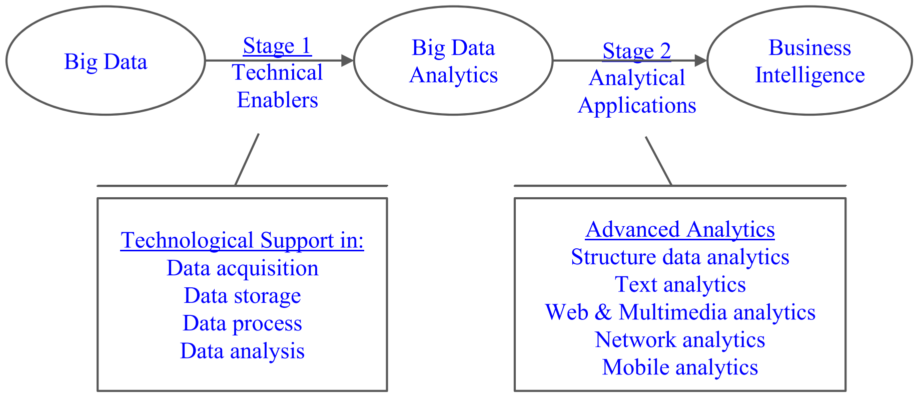

Fig. 1. Road map to review studies on big data, BDA and business intelligence.

(1984) emphasises that better analytical tools with enhanced capabilities are the keys to improving analysis and thus decision-making. The review suggests that advanced analytics techniques can improve efficiency at each stage of the BDA workflow. Indeed, new techniques have been constantly proposed and discussed in fields such as computer science and engineering. These techniques can help achieve better data quality, adequate storage space, faster access and process speed, deeper analysis and more concise results presentation. In the following discussions, various techniques are introduced based on analytics workflow structure and around a theme of analytics efficiency.

4.1. Big data acquisition

The review revealed that sources generating data have become more diversified and massive data may come from enterprise business, networking, scientific experiments and others (see Hu et al., 2014). Data acquisition not only concerns extracting raw data from data sources, but includes collection, transmission and pre-processing of data (Chen et al., 2014; Hu et al., 2014; Tsai et al., 2016). Khan et al. (2014a, 2014b) also indicate that data collection, filtering and classification are the main tasks at this stage. Facing massive data, targeting useful data and cleaning the data are particularly vital. Through these steps, analytics can be performed on data with better quality by adopting advanced techniques in the acquisition.

To retrieve raw data generated from various sources, new techniques are developed. A few commonly used methods seen in literature include log files (e.g., Moreta and Telea, 2007; Nicholas and Huntington, 2003; Suneetha and Krishnamoorthi, 2009; Thelwall, 2001b), sensors (e.g., Jonsson and Eklundh, 2002; Luo et al., 2009; Wang and Liu, 2011), web crawlers (e.g., Choudhary et al., 2012; Kaplan and Haenlein, 2010; Thelwall, 2001a), mobile devices (Baak et al., 2013; Kaplan and Hegarty, 2005; Laurila et al., 2012) and RFID (Roberts, 2006). The distributed architecture is normally used to capture system log, and web crawler is often used for unstructured network data (Liu et al., 2013).

Data transmission refers to transporting the data into a data storage infrastructure or data centre. It has IP backbone transmission and data centre transmission. The inter-DCN (e.g., Ghani et al., 2000; Shieh, 2011) and intra-DCN (e.g., Barroso et al., 2013) allow mobility of data within or between storage devices. A final step and a key to improving data quality is data pre-processing, which requires data integration (e.g., Gravano et al., 2003; Lenzerini, 2002), cleansing (e.g., Jeffery et al., 2006; Maletic and Marcus, 2000) and redundancy elimination (e.g., Hussain et al., 2010; Sarawagi and Bhamidipaty, 2002; Tsai and Lin, 2012). It helps aggregate data into a uniform format and improves data consistency. The processed data have benefits in BDA due to reduced costs and increased availability (Chaudhuri et al., 2011).

4.2. Big data storage

One key observation is that data volume is experiencing spectacular growth, which raises the standard for data storage in terms of space and ease to access. The review indicates that advanced data storage techniques can help maximise storage space using a distributed or a networked infrastructure and help save costs and time by conducting analysis within the database or memory (Lv et al., 2017). Data storage capabilities rely on hardware infrastructure, database and management and programming models (Hu et al., 2014). To store larger data sets, hardware infrastructure have advanced to networking architecture, such as direct attached storage (DAS), network attached storage (NAS) and storage area network (SAN) (e.g., Barker and Massiglia, 2002; Chen et al., 2014; Gibson and Van Meter, 2000; Khan et al., 2014a, 2014b; Reed et al., 2000; Shiroishi et al., 2009; Telikepalli et al., 2004). These storage facilities connect to each other or link to a network, which gives easier access to other storage space. Moreover, distributed storage frameworks such as Google GFS and Hadoop HDFS have advantages in dealing with large data sets and steaming data with cheaper disk drivers (e.g., Ghemawat et al., 2003; Shvachko et al., 2010). Data are broken down into smaller scales and distributed in different servers, which enables scalability for processing.

As for the database to store and manage data, RDBMS is mainly for large structured data sets (Moniruzzaman and Hossain, 2013; Ramakrishnan and Gehrke, 2000).

For non-relational databases, there are three major types: key-value database, document database and column-oriented database. It is faster to retrieve data with key and value pairs and easier to compress data and operate parallel processing with data records in a sequence of columns (e.g., Cattell, 2011; Chodorow, 2013; DeCandia et al., 2007; McCreary and Kelly, 2013). In-memory (e.g., Hahn and Packowski, 2015; Watson, 2014) and in-database (e.g., Chaudhuri et al., 2011; Russom, 2012) techniques enable data processing and analysis within memory or the database instead of transporting data between the data centre and disks. In addition, public or private clouds infrastructure help facilitate data management. Resources in clouds can be allocated dynamically, but this raises security concerns (e.g., Assunção et al., 2015; Bi and Cochran, 2014; Talia, 2013).

4.3. Big data processing

Elgendy and Elragal (2014) identify four requirements of processing big data: fast data loading, fast query processing, highly efficient utilisation of storage space and strong adaptability to highly dynamic workload patterns. The review found that timely processing techniques can speed up data processing and enhance the efficiency of large-scale data analytics. Researchers have begun to examine a range of big data techniques such as generic processing model (Condie et al., 2010; Dean and Ghemawat, 2008, 2010; Grolinger et al., 2014; Sagiroglu and Sinanc, 2013), stream processing model (e.g., Cherniack et al., 2003; Neumeyer et al., 2010; Stonebraker et al., 2005), and graph processing model (Lumsdaine et al., 2007; Malewicz et al., 2010; Salihoglu and Widom, 2013). The latter two can deal with large-scale data using graph and event nodes.

In terms of querying, compared to relational processing that uses Structured Query Language (SQL) to access structured data in the relational database (e.g., Pedersen and Jensen, 2001), parallel processing can perform more efficient queries. Data are spread across many servers, and computing problems are solved on separate servers in parallel. No memory or resources need to be shared across different servers, and it is easy to expand with additional servers. It is highly efficient for large-scale data sets and unstructured data (e.g., Jordan and Alaghband, 2002; Parhami, 2006; Roosta, 2012).

4.4. Big data analysis

Data analysis seeks to "understand the relationships among features" and "develop effective methods of data mining that can accurately predict future observations" (Khan et al., 2014a, 2014b, p. 10). It can be descriptive, predictive and prescriptive (Hu et al., 2014). The review revealed that three broad categories of techniques have also been adopted in big data analysis. Mature analysis methods including regression and statistical analysis have been used in advanced analytics, and they are widely adopted in analysing large data clusters. Furthermore, new approaches are emerging, and growing adoption of the advanced methods has been seen in BDA to facilitate decisions.

In particular, data mining (see Han et al., 2011; Witten et al., 2011; Wu et al., 2008) and machine learning (Singh, 2014) are gaining popularity. Given the fact that big data are large in volume and diversified in format, data analysis relies more on computational algorithms to conduct in-depth examinations. Najafabadi et al. (2015) point out that deep learning algorithms benefit extracting information from massive data. Moreover, to present the massive amount of data and analysis results, more concise and interactive methods and platforms are required, such as advanced data visualisation (ADV). These platforms are relatively new in business intelligence and analytics, but they are helpful in give data users better engagement with data analysis and interpretation.

5. Big data analytics techniques in management application

Having set out the various advanced techniques in data analytics workflow, this section relates to BDA mainly in management disciplines. Following the classification approach in Chen et al. (2012), we group the literature based on various data types: structured data, text, web and multimedia data, network data and mobile data. The review indicates that techniques for structured data analytics have seen tremendous improvements. Novel platforms and advanced analytics have been developed, while several mature programs in current business intelligence system continue serving in BDA by continuously optimising the designs for handling large volume data. The review also reveals that current research emphasises unstructured data analytics, and the majority of previous studies apply advanced techniques to analyse big data for enhancing management effectiveness.

In the business intelligence 1.0 system (Chen et al., 2012), data are mostly structured with pre-defined index or primary keys indicating relationships of data entities. In business intelligence 2.0 and 3.0 systems, data are generated with faster speed and greater diversity, which requires new analytics techniques to meet new challenges in structured and unstructured data analytics. Given the significant interest in unstructured data analytics in the current business intelligence and analytics research (Chen et al., 2014; Hu et al., 2014), our discussions underscore such importance by discovering major themes in management-related big data research.

5.1. Text analytics

A considerable stream of research investigates the topic of text analytics (see a detailed summary of literature in Appendix A). In our literature sample, many studies target text mining, clustering and classification to detect topics and opinions, personalisation and recommendations and other areas. Text analytics depends largely on text mining, which deals with unstructured text from documents, emails, logs, web pages, social media, comments, feedback and so on. In this process, document representation and query processing help retrieve information, while Natural Language Processing (NLP) detects certain words, phrases, events and topics from massive data. Then the processed data can be used to construct models for further analysis, such as topic models (e.g., Blei, 2012), language models (e.g., Kao and Poteet, 2007), sentiment or opinion mining (e.g., Garg and Chatterjee, 2014; Ibrahim et al., 2017; Pang and Lee, 2008), interactive question and answer systems (e.g., Fan et al., 2006a, 2006b). Hence, information retrieval and statistical NLP are the bases from which more text-based searching and analysing techniques are innovated. These novel approaches can serve as techniques for other emerging research such as web and network analytics.

5.2. Web and multimedia analytics

Web analytics has become an essential part in Web 2.0 systems (O'Reilly, 2007). It aims to discover and analyse useful information from web documents and services such as web text, link structure, web logs and other types of web data (Ashton et al., 2013). The review found that web mining is a big part of web analytics (see Table 1). The web content, structure and usage mining data (Pal et al., 2002) provide abundant information about user dialogues and behaviours (e.g., clickstream), which is useful for improving business operations, particularly for improving the efficiency of marketing activities in electronic commerce.

In addition to web data presented in text format, other information contained in images, audio and video is becoming new research objectives. Current research mainly concentrates on the multimedia summarization (Ding et al., 2012), multimedia annotation (Wang et al., 2012), multimedia index and retrieval (Lew et al., 2006) and multimedia recommendation (Park and Chang, 2009). These techniques help extract hidden information from images, audios and videos with proper classification, annotation and retrieval, which can be used with other web and media data to suggest particular content to users based on their preference. However, we noted a handful of studies using multimedia data for gaining business insights, which lags behind other data exploration. It may due to the richness of content, which causes difficulties in extracting information and organising it into structured data.

5.3. Network analytics

Network science has evolved with the rapid growth of online interactions and online social networking since 2000. Such massive amounts of user-generated data often reflect consumers' opinion and connections. The review illustrates that social media analysis seems to be a promising direction in big data research. Many studies use social media data to discover consumers' sentiment, predict consumers' behaviour, detect relationships and influences in the online community and enhance brand and sale performance (see Appendix B). Discovery of potential links, social influence and interactions in the network is helpful for understand the preferences, behaviours and dynamics in the virtual community.

5.4. Mobile analytics

Mobile devices are penetrating universally, and mobile computing technologies enable millions of applications to generate a vast amount

Table 1
List of studies on web and mobile analytics.

	Analytics	Studies	Key area
Web	Web mining	Baek et al. (2012)	Online reviews
		Castellanos et al. (2012)	Streaming data analytics
		Chau and Chen (2008)	Web page classification
		Chau and Xu (2007)	Online community
		Chung et al. (2005)	Knowledge discovery
		Costa et al. (2012)	E-commerce
		D'Haen et al. (2013)	Predict profitability
		Ding et al. (2015)	Real-time analysis
		Ho et al. (2011)	Personalisation
		Költringer and Dickinger (2015)	Destination brand
		Shahabi and Banaei-Kashani (2003)	Personalisation
		Thorleuchter and Van den Poel (2013)	Idea mining
		Wang et al. (2007)	Web content mining
		Yeh et al. (2009)	Customer prediction
		Sonnier et al. (2011)	Online communication
	Web analytics	Järvinen and Karjaluoto (2015)	Digital marketing
		Kou and Lou (2012)	Web search engines
		Lau et al. (2012)	International investment
	Clickstream	Chatterjee et al. (2003)	Online advertising
		Montgomery et al. (2004)	Personalisation
		Schäfer and Kummer (2013)	E-commerce
		Huang and Van Mieghem (2013)	Inventory management
	Cloud computing	Marston et al. (2011)	Business-related issues
		Delen and Demirkan (2013)	Service orientation
		Guo et al. (2014)	Apparel manufacturing
		Zissis and Lekkas (2011)	E-government
Multimedia	Image retrieval and annotation	Lee and Wang (2012)	Geographic knowledge discovery
		Lee et al. (2011)	Analytics technique
		Liao et al. (2014)	Analytics technique
		Yang and Lee (2008)	Image semantics
	Video data	Zhang et al. (2014)	Social influence
Mobile	Mobile sensing	Andrews et al. (2016)	Mobile advertising
		Fong et al. (2015)	Mobile targeting
		Ghose et al. (2012a, 2012b)	Mobile Internet usage
		Lee (2007)	Personalisation
		Li and Du (2012)	Mobile advertising
		Li and Wang (2017)	Food supply chain
		Luo et al. (2014)	Mobile targeting
		Yang et al. (2008)	Recommendation
	Mobile network	Chung et al. (2015)	Personalisation
		Ghose and Han (2011)	Mobile Internet usage
		Wang et al. (2013a, 2013b, 2013c)	Market dynamics
	Mobile app	Ghose and Han (2014)	Mobile apps demand
		Xu et al. (2014)	Online media

of information. Mobile and sensor-based systems foresee a promising future in business intelligence and analytics (see Table 1). Gathered from applications embedded in smart devices such as smartphones and tablets, data generated from these sources are usually fine-grained, location-specific, context-aware and highly personalised. The review shows that typically, mobile analytics uses mobile sensing, web logs, networking and applications to acquire personalised data from mobile users and create behavioural models of individuals to realise customised advertisements or recommendations. It provides great opportunities to innovate and advance understanding of markets and customers in a timely manner.

6. Discussions and concluding thoughts

Although the last ten years has witnessed a surging stream of research on big data, BDA and business intelligence, limited attention has been paid to harnessing big data to improve managerial and economic decisions. This study sought to fill this void by reviewing the literature on BDA across the social sciences and thus shed light on how data have been utilised in different settings. The paper identified 280 studies published in the past 16 years and classified them with a structured scheme. This review does not claim to be complete, given the fast growing body of research in relevant areas. In reflecting on Professor Ayre's contributions, we saw the need to extend his works by incorporating the richness of big data research. Clarifying the current knowledge of advanced analytics techniques benefits future application of BDA in the business sector. This study serves as the link between our survey of literature and Professor Ayres' emphasis on the role of technology in making better decisions. Within the review scope, an investigation into the collected studies led to the identification of two dimensions in current BDA research. From a technical perspective, studies focus on the analytics workflow, in which advanced techniques can help improve efficiency in handling big data. From a managerial perspective, advanced techniques target diversified data types and sources and are used in business analytics to achieve better managerial insight.

The review of the multi-disciplinary literature on BDA techniques and their applications further revealed several underexplored areas. One key observation in this review is that among the four topics in unstructured data analytics, text analytics and network analytics seem to be more attractive to management researchers than web, multimedia and mobile data techniques. This may be a result of the growing number of users on social media platforms (e.g., Facebook and Twitter) and accessibility of the data sources that sparks such big data research (Chan et al., 2017; Mount and Martinez, 2014; Rapp et al., 2013). While text and network analytics are popular, analysis of web data, audio, video, mobile and sensor data are rarely seen in general management studies. Nevertheless, other types of unstructured data are also being generated and collected on an astronomical scale across various industry sectors, and most organizations have more data than they know how to use effectively (LaValle et al., 2011).

Perhaps the most prominent gap in the current literature is the limited attention paid by scholars in information science and management science to the potentials of harnessing BDA to achieve competitive advantage. One shortcoming we spotted is that the majority of studies have been conducted by scholars in areas such as marketing and operations management. Information management has yielded a large number of papers proposing novel approaches to handling big data, and the applications of these techniques are seen in marketing and operations research. Studies in this area cannot flourish in isolation and require research inputs from other management disciplines such as strategy, innovation, entrepreneurship, international business, organization and sector studies. Therefore, research is needed to advance further understanding and utilisation of BDA in managerial applications. Nonetheless, in other management subjects, the influence of big data on the performance of management is understudied and offers promising avenues for future research. Similarly, there is an urgent need for closer collaborations between the academics and the industry to advance big data research and applications.

In addition, empirical and modelling papers are in the majority of studies reviewed, which tend to utilise advanced techniques and propose novel approaches to processing big data. The volume, variety and velocity characteristics of big data require a combination of interdisciplinary knowledge and a mixed methodological approach to

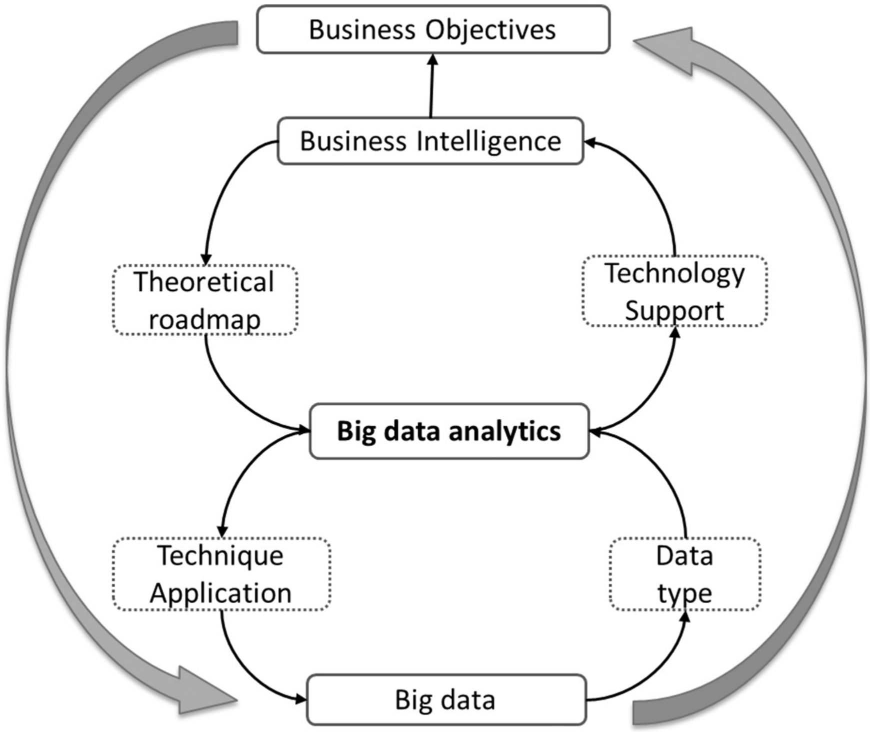

Fig. 2. Framework for big data research.

address the challenges of using it (Chan et al., 2016). Despite the fact that big data research has seen rapid growth in management disciplines, it is still at an early stage and many key questions remained unanswered.

Big data analytics can empower businesses to perform better predictive and prescriptive analysis to forecast and plan for the future, which are essential for management to make accurate decisions (see also Ayres, 1989). To guide future research, a framework is proposed to identify opportunities (see Fig. 2). In this cycle, big data, BDA and business intelligence are linked, and research opportunities can be explored from two alternative routes. One is the top-down strategy. Guided by the business objective and intelligence desired, proper analytics techniques can be selected based on big data theory and applied to available data sets, which will help make better use of big data. On the other hand, a bottom-up strategy indicates that research can start with sorting out available big data and then analysing it with suitable techniques and technology support to gain valuable insights, thereby ultimately making an impact on business decisions and performance.

One limitation of this study is the selected scope using a keyword search approach. It may omit some earlier studies that might not use certain keywords that were not popular at that time. Future research opportunities can be identified in each element and linkage in this framework, which can help identify new research interests and may also offer implications for enterprises to take advantages of big data.

Table 2 proposes several unanswered questions in present BDA research in management field. Among them, we think the priority should be developing a clearer picture of big data potentials and BDA methods. Given that there is a lack of theories and conceptual maps to instruct researchers around big data themes, guidance on how to leverage big data and analytics techniques for achieving business intelligence are in urgent need to systematise the research with solid theoretical foundations. In honour of Professor Robert Ayres' contributions to research in technological forecasting and social change, we hope that this study can serve as a useful reference point for researchers in management fields to advance big data research, forecasting and applications of BDA.

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Table 2
Unanswered questions for future research.

Area	Key theme	Unanswered questions
Big data	Structured data	1. To what extent can conventional techniques be applied to big structured data? 2. How can structured data be effectively combined with unstructured data to design business strategy?
	Unstructured data	3. How can unstructured data be effectively utilised to address business problems? 4. What is the most effective method to concurrently analyse both structured and unstructured data?
Big data analytics	Technique improvement	5. To what extent does an advanced technique improve the effectiveness of analytics? 6. What is the most effective mechanism to assess and compare the effectiveness of different analytics techniques?
	Technique application	7. How best to transfer and apply techniques in computer science, engineering and other technological subjects into analysing big data for general management?
Business intelligence	Theoretical road map	8. What are the main steps for adopting big data in enterprise business intelligence process? 9. What are influential paths and mechanisms for value creation in organizations?
	Technological support	10. How best to incorporate advanced analytics techniques into current business intelligence system to improve BDA ability? 11. What is the most appropriate business intelligence platform for firms?

Appendix A. List of studies on the topic of text analytics

Studies	Key area/application	Key findings
Aliguliyev (2009a)	Document clustering	By signing weights, document clustering can be improved and thus the performance of search engines.
Aliguliyev (2009b)	Document summarization	The sentence-clustering based method improves document summarization performance.
Archak et al. (2011)	Consumers reviews	The textual content of product reviews has a significant impact on consumers' choices, which can be used for predicting future sales.
Balakrishnan et al. (2010)	Capital market	Narrative disclosure has value-relevant information to predict market performance.
Bao and Datta (2014)	Risk type evaluation	Risk types can be measured with corporate textual data of risk disclosure.
Baralis et al. (2013)	Document summarization	The proposed method can effectively perform ontology-based analysis of document sentences.
Beebe et al. (2011)	Analytics technique	The extended approach to digital forensic text string search process improves information retrieval effectiveness.
Cao et al. (2011)	Online reviews	More helpfulness is found in reviews with extreme opinions than in those with mixed or neutral opinions.
Chen and Tseng (2011)	Quality evaluation	The proposed method can effectively evaluate review quality and thus improve opinion mining efficiency.
Chou et al. (2010)	Analytics technique	Combining filter and wrapper attribute selection approaches provides more efficient and accurate classification results.
Chung and Tseng (2012)	Product review	The proposed framework can effectively detect the relationship between reviews and ratings.
Colace et al. (2014)	Analytics technique	A single label text classification method performs better when labelled examples are limited.
Coussement and Van den Poel (2008)	Churn prediction	Textual information in emails is beneficial to improve churn prediction performance.
Crawford Camiciottoli et al. (2014)	Brand associations	Consistent brand associations are detected in an online community of international consumers.
Delen and Crossland (2008)	Literature survey	Text mining is of great use to analyse textual information and identify patterns of research topics.
Duan et al. (2011)	Analytics technique	This is an effective approach to extract bilingual multiword expression.
Fan et al. (2006a, 2006b)	Personalisation	Online information routing of personalised information can be improved with the two-stage model.
Fuller et al. (2011)	Deception detection	Text and data mining are combined to automatically detect deception with better accuracy.
Glancy and Yadav (2011)	Fraud detection	A computational fraud detection model on textual data is effective for detecting financial fraud in reports.
Guerreiro et al. (2016)	Cause-related marketing	Text mining techniques can help review literature and uncover topics.
Hashimi et al. (2015)	Selection criteria	A set of criteria is proposed to evaluate the effectiveness of different text mining techniques.
He (2013a)	Online interaction	Video stream data are used to identify patterns in online learning behaviours.
He (2013b)	Case-based reasoning	Text mining and Web 2.0 tools can be beneficial to CBR systems with a better user experience.
Hu et al. (2012)	Online reviews	Manipulation by firms is found in online reviews, particularly in product ratings.
Hyung et al. (2014)	Music recommendation	Analysing listeners' text from a radio station's online bulletin board is beneficial for recommending music.
Janasik et al. (2009)	Research method	SOM enables better effectiveness of text mining to improve inference quality in qualitative research.
Kayser and Blind (2016)	Foresight practice	Text mining contributes to foresight by broadening the knowledge base.

Krishnamoorthy (2015)	Online reviews	The proposed model based on linguistic features can achieve better predictions of online review helpfulness.
Lee and Bradlow (2011)	Market structure analysis	The proposed system automatically processes text from online reviews and improves marketing strategy.
Li et al. (2015)	Process mining	The proposed method improves data extraction and task identification from event logs.
Lo (2008)	Web service quality	Text analysis helps in classifying customers' messages and identifying service quality.
Ludwig et al. (2013)	Online reviews	Powerful reviews should be identified, encouraged and promoted with typical linguistic style.
Ludwig et al. (2014)	Community identification	Linguistic style match in user communities indicates community identification and fosters greater participation quantity and quality.
Martínez-Trinidad et al. (2000)	Analytics technique	The tool is used for detecting themes in documents. High co-occurrence between two concepts implies strong relationships.
Moon et al. (2014)	Product review	Analysing text of consumers' product reviews can enhance sales.
Moro et al. (2015)	BI in banking	Text mining is used to review the literature on business intelligence application in banking.
Mostafa (2013)	Brand sentiment	Tweets are used to detect consumers' sentiments, and a general positive attitude is found in the sample.
Nassirtoussi et al. (2014)	Market prediction	The review identifies a clear frame of discussion on market prediction using online text mining.
Nassirtoussi et al. (2015)	Market prediction	A multi-layer algorithm integrates sentiment analysis to tackle textual information with a focus on financial market prediction.
Netzer et al. (2012)	Market structure analysis	Online user-generated contents can improve mapping of market structure.
Ngo-Ye and Sinha (2014)	Online reviews	Review text and reviewer engagement characteristics can predict the helpfulness of online reviews.
Noh et al. (2015)	Patent analysis	Keyword strategies of text mining can be applied for patent analysis with better validity and reliability.
Ordenes et al. (2014)	Customer feedback	The advanced linguistic-based text mining model can more deeply analyse customers' experiences.
Özyurt and Köse (2010)	Chat mining	Mining chat conversations using proposed classification can effectively detect topics.
Singh et al. (2014)	Employee blogs	Textual characteristics of blogs affect readers' attention and retention, which can help improve understanding of reading behaviour in communities.
Suh et al. (2010)	Petition trend forecast	Text and data mining are combined to efficiently detect and forecast trend of the petition in e-government.
Sunikka and Bragge (2012)	Research profiling	Text mining is applied to review the literature on personalisation to identify future research opportunity.
Tang and Guo (2015)	Electronic word-of-mouth	Linguistic indicators from text can predict word-of-mouth attitudes about products and services.
Thorleuchter and Van den Poel (2012)	E-commerce	Textual information on companies' websites is useful for predicting commercial success.
Thorleuchter et al. (2010)	Idea mining	An idea mining approach is proposed to automatically discover new ideas from textual information.
Thorleuchter et al. (2012)	Profitability prediction	Current customers' website information can be used to identify future profitable customers more accurately.
Ur-Rahman and Harding (2012)	Analytics technique	Classification accuracies are improved by classifying textual data into different classes.
Wang et al. (2013a, 2013b, 2013c)	Online reviews	A web-based system can automatically extract and summarize information from review documents.
Wei et al. (2006)	Document clustering	The personalised document-clustering approach can achieve better clustering effectiveness.
Wei et al. (2007)	Query expansion	A topic-based method for query expansion is more effective for addressing word mismatch problem in information retrieval.
Wei et al. (2008a, 2008b)	Knowledge map	It is effective to generate knowledge maps using the multilingual document clustering method.
Wei et al. (2008a, 2008b)	Personalisation	Better effectiveness and personalisation are achieved by the extended document-clustering technique.
Weng and Liu (2004)	E-mail responding	Different concepts are integrated into classification to effectively extract information and reply e-mails.
Yang (2009)	Web page annotation	The proposed methods can automatically generate metadata for the web page for semantic analysis.
Yang and Lee (2004)	Web directories	The corpus-based method automatically and efficiently illustrates web directory hierarchy with labels.
Yoon (2012)	Weak signal detection	Keyword-based text mining is useful for identifying weak signal topics for future business planning.
Zeng et al. (2010)	Analytics technique	A multi-grain hierarchical topic structure that can provide a description for subtopics outperforms other methods.
Zhan et al. (2009)	Online reviews	Text in online product reviews can be automatically summarized based on internal topic structure.

Zhang and Jiao (2007)	Recommendation and e-commerce	The proposed associative classification-based recommendation system can be applied for personalisation in B2C e-commerce application.

Appendix B. List of studies on network analytics

Studies	Key area/ application	Key findings
Social media analysis		
Abrahams et al. (2014)	Quality management	Social media content and text are of great use for product defect discovery.
Beverungen et al. (2015)	Free labour	Social media users working as free labour challenges Marxist organization studies.
Chan et al. (2017)	Operation management	Social media comments are analysed to discover useful information for operations management.
Chan et al. (2016)	Analytics technique	A mixed approach to analysing social media data can enhance operational decision-making.
Claussen et al. (2013)	Mobile apps success	App success relies on rewarding users' engagement, high user ratings and frequent updating.
Feuls et al. (2014)	Unemployment	Use of social media can help unemployed people to maintain and cultivate social networks.
Gao et al. (2015)	Emotion analysis	A rule-based approach is proposed to detect emotion-causing component from social media data.
Ghose et al. (2012)	Ranking system	The proposed ranking system analyses user-generated content to assess customers' preferences and can provide best-value hotels.
Gopinath et al. (2013)	Blogs and advertising	The effects of pre- and post-release blog and advertising vary across markets with different demographic characteristics and groups.
He et al. (2015)	Marketing	Competitive social media analysis with sentiment benchmarks is beneficial to marketing.
Iyer and Katona (2016)	Marketing	The incentives for social communication in social media decrease with an increased span of communications.
Jang et al. (2013)	Deep sentiment analysis	The proposed method can determine customers' value structure and causality for identifying a niche market.
Kim et al. (2015)	Forecasting earning	Social network information and a machine learning algorithm can improve forecasting accuracy.
Li et al. (2014)	Targeted advertising	The effectiveness of advertisement can be enhanced by leveraging social context and social influence.
Luo et al. (2013)	Firm equity value	Social media metrics significantly indicate firms' equity value with stronger and faster predictive relationships than traditional online behavioural metrics.
Mayzlin and Yoganarasimhan (2012)	Web logs linking	Blogs with links to other blogs signal as high news-breaking ability and lead to more readers and enhanced learning.
Miller and Tucker (2013)	Business value of IT	Social media management in health-care sector leads to more user-generated content by employees, and it may have adverse effects.
Moe and Trusov (2011)	Online product rating	Online product ratings dynamics have direct and immediate effects on sales and indirect impact on further ratings.
Mount and Martinez (2014)	Open innovation	Social media has benefits to be applied to the open innovation process.
Nam and Kannan (2014)	Brand performance	Social tagging has great implications for brand performance measurement and brand equity management.
Nguyen et al. (2015)	Brand innovation	Social media strategic capability can enhance brand innovation and moderate between innovation, knowledge acquisition and market orientation.
Oestreicher-Singer and Sundararajan (2012)	Recommendation	Demands increase with explicit visibility of a co-purchase relationship in a recommendation network.
Okazaki and Taylor (2013)	International advertising	Three theoretical foundations are identified for future research on social media use for international advertising.
Orlikowski and Scott (2013)	Online evaluation	Online and traditional valuation is significantly different in performativity, which has organizational implications.
Prates et al. (2013)	Web search engines	Social media data are adopted to improve contextual information extraction through web searching.
Rapp et al. (2013)	Contagion effect	Positive contagion effects of social media use are found in enhancing brand performance, retailer performance and consumer-retailer loyalty.
Roth et al. (2013)	Personnel decision	The use of social media in human resources practice has great importance for organizations, individuals and society and needs further study.
Sabnis and Grewal (2015)	Competition	There is a significant relationship between competitor user-generated content and firms' performance.
Schniederjans et al. (2013)	Impression management	Social media has a positive impact on impression management and can influence firms' financial performance.
Schweidel and Moe (2014)	Brand sentiment	

		The analysis of brand sentiment cannot ignore the differences across different social media venue formats.
Shriver et al. (2013)	Social network analysis	Online user-generated content has a positive relationship with their social ties, and it has network effects that boost advertising and revenue growth.
Singh et al. (2011)	Analytics technique	The proposed method of sampling qualitative comments improves the effectiveness of text mining.
Sun (2012)	Product rating	A higher variance of product ratings helps with sales increase if and only if the average rating is low.
Tirunillai and Tellis (2014)	Brand performance	Dynamic analysis of online user-generated content can reflect consumers' satisfaction with the quality and thus improve competitive brand positions.
Van Iddekinge et al. (2013)	Personnel decision	Social media information of job applicants is irrelevant and invalid to recruitment selection.
Wu (2013)	Social network effect	Social media can enrich network information, which has a positive effect on work productivity and job security.
Social network analysis		
Autio et al. (2013)	Entrepreneurial action	Online user community information about users' needs can stimulate entrepreneurial action.
Fang et al. (2013)	Adoption probabilities	The method can effectively predict adoption probabilities based on key factors that affect adoption decisions.
Garg et al. (2011)	Information diffusion	Information diffusion and discovery in online social networks are effectively measured using proposed methods.
Ransbotham et al. (2012)	Information value	The value of collaborating user-generated content depends on contributors' efforts as well as their network.
Wang et al. (2013a, 2013b, 2013c)	E-commerce	Social network analysis and web mining are integrated to detect groups in virtual communities for better recommendations and marketing.
Community detection		
Feng et al. (2015)	Personalisation	A time-weighted overlapping community detection method performs better to predict users' interests and thus give personalised recommendations.
Johnson et al. (2015)	Leadership	Use of language shapes online community dynamics. Similar use is found from leaders and other participants.
Social influence		
Berger (2014)	Word of mouth	Word of mouth is goal-driven and has five key functions with psychological factors behind them.
Cascio et al. (2015)	Consumer behaviour	People tend to change their initial recommendation decisions to be consistent with peer recommendations.
Cheng and Ho (2015)	Online reviews	There is a positive impact of reviewers' number of followers, level of expertise, image count and word count on readers' perceptions of reviews.
Eisingerich et al. (2015)	Word of mouth	Consumers' willingness to engage in word-of-mouth on online social sites is lower than face-to-face WOM.
Goes et al. (2014)	Online community	Popular users in online community tend to generate more objective, negative and varied product reviews.
Goh et al. (2013)	Brand community	Users' and marketers' engagement in social media brand communities has a positive impact on purchase behaviour and expenditures.
Haenlein (2011)	Customer relations	There is a strong positive social network relationship in customer-level revenue.
Hennig-Thurau et al. (2014)	Microblogging	A microblog containing post-purchase quality evaluation information affects early movie adoption behaviours.
Hildebrand et al. (2013)	Consumer satisfaction	Feedback on product features from other community members has a negative influence on customers' satisfaction with self-designed products.
Kurt et al. (2011)	Consumer behaviour	Agency-oriented consumers spend more when shopping with friends, while communion-oriented consumers do not.
Lee et al. (2015)	Online rating	Prior ratings by friends positively influence users' ratings, while social networking decreases possible effects on ratings by the crowd.
Lu et al. (2013)	Opinion leadership	The activity of the online community and style of writing the review are strong drivers for network growth.
Sridhar and Srinivasan (2012)	Online ratings	The online rating has a social influence on other consumers that is contingent on product experience.
Sentiment analysis		
Alfaro et al. (2013)	Opinion mining	Opinion trends can be detected from weblog comments, providing useful information for decision-making.
Balahur et al. (2012)	Emotion detection	When words have no affective meaning, an approach using EmotiNet is more valid for emotion detection.
Colace et al. (2015a, 2015b)	Recommendation	User-generated data in the online social network can support customised recommendations.
Colace et al. (2015a, 2015b)		

	Analytics technique	The proposed method uses a mixed graph of terms that yields more effective sentiment classification.
Da Silva et al. (2014)	Microblogging	Classifier ensembles can improve classification accuracy of microblogging sentiment analysis.
Das and Chen (2007)	Sentiment extraction	Small investor sentiment from stock message boards is related to stock value and has an impact on investors' opinions and financial management.
Dehkharghani et al. (2014)	Causal rule discovery	Sentiment causal rules effectively summarize important relationships and sentiment from social media textual data.
Deng et al. (2014)	Term weighting	The supervised term-weighting approach gives more accurate results in sentiment analysis.
Fang et al. (2014)	Sentiment classification	The proposed approach with sentiment information from source-domain labelled data and preselected sentiment works is proved efficient.
Fersini et al. (2014)	Polarity classification	Ensemble learning is introduced to predict polarity with better accuracy.
García-Cumbreras et al. (2013)	Collaborative filtering	Sentiment analysis incorporated in collaborative filtering algorithms improves rating prediction and recommendation.
García-Moya et al. (2013)	Analytics technique	The proposed system allows analysing sentiment data in the corporate data warehouse.
Gopaldas (2014)	Consumer sentiment	The proposed theory of marketplace sentiments advances studies on consumers with a sociocultural perspective.
Homburg et al. (2015)	Marketing performance	Firms' active participation in the online community among consumers has a negative impact on consumers' sentiment and returns.
Kang and Park (2014)	Customer satisfaction	Customers' satisfaction can be measured by customers' reviews with greater effectiveness and efficiency.
Khan et al. (2014a, 2014b)	Microblogging	The proposed hybrid approach can achieve higher accuracy in sentiment classification.
Kontopoulos et al. (2013)	Microblogging	An ontology-based method is more efficient for analysing opinions towards specific topics in microblogs.
Li and Wu (2010)	Forums hotspot detection	The proposed method can improve hotspot detection and forecast from online forums.
Marrese-Taylor et al. (2014)	Opinion mining	The aspect-based opinion mining approach can be used in tourism product reviews with extension.
Musto et al. (2015)	Social streams	The proposed framework can effectively process semantic analysis of textual content in social streams.
Ye et al. (2009)	Sentiment classification	Well-trained machine learning algorithms can classify sentiment polarities of reviews with high accuracy.
Yu et al. (2013)	Firm equity value	Social media has greater effects on firm stock performance than conventional media.

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