Big Data Evaluation Scorecard

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Abstract

This study seeks to examine the evolution of issues that have been espoused by both junior and senior scholars to aggregate out of literature, a criterion that can guide firms in evaluating their Big data analytic (BDA) projects. The systematic review approach took stock of varied socio-technical understanding, requirements, and capabilities used in addressing Big data issues and synthesized these issues for value accruals.

The study strongly argues that Big data benefits accrue to firms whose economic activities require distributed collaborative effort, operational visibilities, cost, and time-sensitive decisions who adopt and implement the concept in their strategic, tactical, and operational levels. Though the trend shows steady growth in scholars' interests and expectations in BDA, a significant percentage of the reviewed studies were not informed by any theory. The study contributes to BDA literature by affording scholars issue gaps and for practitioners, an analytical competency and evaluation scorecard that links strategic business goals to operational outcomes.

Keywords: Big data analytics, socio-technical challenges, analytical scorecard

Big Data Evaluation Scorecard

1. Introduction

Recent capabilities to process and derive business value from "big data" (BD) has increased the attention and interest of both academia and practice in the phenomena. Existing evidential findings attribute this attention to BD's propensity to transform the narrative of management theory and practice (Chae, Yang, Olson & Sheu, 2014; Mishra, Gunasekaran, Papadopoulos & Childe, 2017). Perhaps, the interest stems from the promise of enhanced decision insights that strategically improve operational agility, enhance performance, and enable expected return from an investment (Kiron, Prentice & Ferguson, 2014).

According to Lyytinen and Grover (2017), BD capabilities provide the necessary data-driven visibility to assist firms in offering unique customized services, detect anomalies before they affect performance, increasing firm growth, and competitive advantage. Quantitatively, IBM asserts that organizations that fully adopt BD are likely to maximize revenue growth by 1.6 times per annum, double their earnings before interest, tax, depreciation, and amortization to appreciate stock price by 250% (IBM Corporation, 2013). Full adoption, according to Ridge, Johnston, and Donovan (2015), spans across the firms' strategic, tactical and operational levels in distributed collaborative works, operational visibility, accurate decisions, and reduction in operational cost and time.

Although the prospects for BD analytics are primarily positive, concerns such as information overload (Whelan &Teigland, 2010), investment not yielding expected benefits in legacy firms, and BD investments accruing dividends after five to ten years of full implementation, have been raised (Bughin, LaBerge & Melbye, 2017; Power, 2016). These challenges informed the call by Ransbotham, Kiron & Prentice (2015) for the better elucidation of the issues, paradigm, theories, and methodologies driving the use of BD in business processes to identify unexplored gaps necessary to explain the phenomenon better.

Regardless of extant BD scholarly review works carried out so far, (Fosso Wamba & Mishra, 2017; Fosso Wamba, Akter Edwards, Chopin & Gnanzou, 2015; Mishra et al., 2018), minimal effort, if any, got invested in developing theories (evaluation criteria) amidst the issues reviewed (Siddaway, Wood, & Hedges, 2019). In a typical literature stock-taking exercise, this paper seeks to bridge the gap identified above by answering the question: How can the current issues, themes, and conceptual approaches in BD literature assist practitioners in evaluating implementation and performance? Specifically, the paper aims to:

- Examine the evolution of issues that have been espoused by both junior and senior scholars to aggregate out of literature, a criterion that can guide firms in evaluating their Big data analytics (BDA) projects and broaden their socio-technical understanding, requirements, and capabilities for BD initiatives.
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The next section of the paper outlines the research approach and the adopted protocol that informed the research boundary. Section 3.0 presents the results of the study, while section 4.0 discusses the research findings, limitations, and future gaps. The final section summarizes and concludes the study.

2. Research Approach and Protocol

Like most studies that are grounded in literature, approaches conceived were narratives, meta-analysis, vote counting, and descriptive analysis espoused by King and He (2006).

However, the authors agreed on systematic review because of its theory development support, the implication for practice (Siddaway et al., 2019), and the ability to aggregate available peered reviewed papers to address the research question (Fahimnia, Sarkis & Davarzani, 2015). Convenience and appropriateness (Petter & McLean, 2009) limited the search for articles to electronic databases. Specifically, the database search encompassed the association of information systems (AIS) electronic library of journal collections, Emerald, Web of Science, Ebscohost, ScienceDirect, and Scopus.

In trying to have a glimpse of recent issues in BD publications, the study restricted reviewed publications span to five years, from 2013 to 2017. The researchers combined key search strings such as 'big data analytics*,' 'business analytics* AND 'Business process*' AND 'Business Intelligence*,' "Advanced Analytics*" AND "Business process*" which resulted in a total of 498 papers. These were manually filtered to eliminate duplications, conference papers, editorials, workshops, notes, and tutorial summaries. Only English peered reviewed completed studies in journal publications from 2013 to 2017 with relevance to the purpose study were considered. A total of 88 publications met the inclusion and exclusion criteria and got reviewed to identify the issues, theory, and methodology.

For example, through the lens of qualitative, mixed-methods, experiments, and quantitative research protocols (Duncombe & Boateng, 2009), the research methodology was classified. Thus, articles that were highly objective with the positivist structured questionnaires for survey research were under the classification "Quantitative" (Babbie, 2011), while methods such as ethnography, hermeneutics, phenomenology, case studies adopting focus group discussions, interviews, and observations got categorized as "Qualitative."

Similarly, studies that complimented the weaknesses with the strengths of both qualitative and quantitative epistemological orientation got classified as "Mixed Method" (Allana and Clark, 2018). The category "Experiment" got assigned to studies that imitated and model real-world events, processes, and operations to unearth new or improve the existing processes. However, studies with no means of identifying their methodological orientation got assigned to "Conceptual" instead of the "No Method" category adopted by Senyo et al. (2018).

2.1 Research themes

Over the years, IS scholars have encapsulated issues in themes to ease theorization. For instance, in analyzing business maturity models, Chen and Nath (2018) had data and analytics technology environment, strategic alignment, top-level sponsorship and support, analytics talents, performance management, and organizational impacts as themes emerging from their review. Similarly, Sivarajah, Kamal, Irani, and Weerakkody (2017) conceptualized Big data challenges under themes such as data challenges, process challenges, and management challenges. However, the authors adopted the IT/IS resource capabilities classification of "human capabilities, technological capabilities, and organizational capabilities" espoused by Ross, Beath, and Goodhue (1996) because it absorbs most taken for granted resource capabilities and implementation assumptions (Marfo, Boateng & Effah, 2017).

2.1.1 Human Capabilities

Human capabilities constitute a blend of requisite IT/IS human expertise and analytical competencies that are coordinated in business knowledge to identify proactive opportunities that resolve challenges at the firm level (Armstrong & Shiminzu, 2007). In order to compete on talent, the human capabilities theme got stratified into three personified actors, namely: the consumers, producers, and enablers (Cosic, Shanks, & Maynard, 2012). Analytical team

members with the requisite competency of linking analytical results to the business use-case logics for daily decision-making insight and value-creating actions known as consumers (Gartner, 2014). Whereas personnel vested with the technical capabilities to code, define domain-specific business rules, analyze data and events to generate descriptive, predictive, and prescriptive analytics reports and dashboards for necessary insight are known as producers (Gartner, 2014). Enablers include system architects, project managers, and data scientists who design, build, implement, and maintain the systems used by consumers (users) and producers (analysts) (Chen, Chiang & Storey, 2012).

2.1.2 Technological Capabilities
This theme includes technological infrastructures, both physical and logical artifacts, designs, and configurations that strategically support the firm's operational, process, and analytical journey from problem identification, data mining, data sourcing, integration, and analysis for insight generation (Chae & Olson, 2013). According to Marfo et al. (2017), this theme combines analytical capabilities, data management capabilities, and infrastructural capabilities. Analytical capabilities deal with the integration of IT enablers, producers, and consumers in understanding and producing tools that shape information delivery (reports and dashboards) and analysis (Isik, Jones & Sidorova, 2011). Data management capabilities include the ability to organize and control within the analytic space, the envisaged problems and opportunities, resources, and processes. It oversees data sourcing, acquisition, processing, and data-sharing aspects of the big data capability agenda (Elgendy & Elragal, 2016). Finally, infrastructure capabilities include everything database technologies, network technologies, and communication artifacts, both hard and software.

2.1.3 Organizational Capabilities
A firms' organizational capabilities drive their fixed and variable investment in strategic structures that respond to both internal and external industry conditions inimical to growth (Minbaeva, 2017). These structures include controls and monitoring systems that continuously optimize routines and practices in conformity with industry benchmarks (Csaszar, 2012). These capabilities align IT/IS risk and responsibility competency with that of business goals to create enterprise-wide shared responsibility, accountability, ownership, and prudent priorities for effective management (Rathnam, Johnsen, & Wen, 2005). Currently, the Information System Audit and Control Association (ISACA, 2008) (ITGI, 2007) provides practitioners with an audit and control framework for firms' IT/IS governance, allowing managers to implement controls that bridge the gap between control requirement, technical issues, data-driven culture, data transparency, ethical concerns, data privacy, and business risk.

3. Presentation of Results
3.1 Search outlets and year of publication
This section analyzes the distribution of articles within a specific repository and the respective year of publication. Scopus recorded the highest number of articles (24 papers), Web of Science recorded (20 papers), AIS electronic library recorded (9 papers), ScienceDirect recorded (13 papers), Ebscohost recorded (12 papers), while Emerald had (10 papers) as represented in Fig. 1.
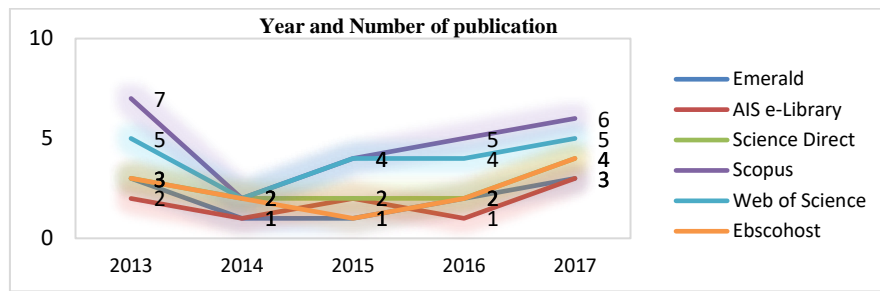
Fig. 1 Distribution of papers by year and repository

3.2 Methodology Distribution

Methodology in every research endeavor seeks to answer the question, "How do we uncover the social reality we seek to study?" (Crotty, 1998). This section examines the methodologies that were adopted to uncover the identified research reality. Of the articles reviewed, the qualitative approach recorded the highest count (40), followed by quantitative (28), Conceptual (3), mixed-method (7), and experiments (10) (see Figure 2).
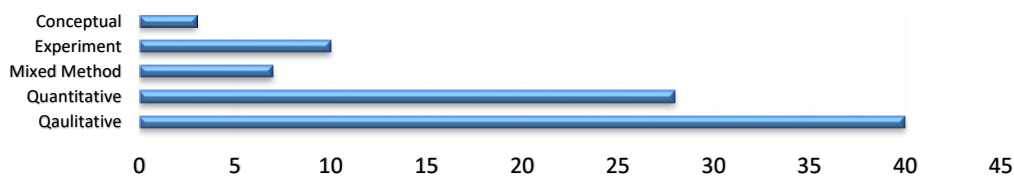

Fig. 2 Methodology Distribution

3.3 Adopted Theories

Most studies derive or build their insights from existing theories (Ravitch & Riggan, 2016). This section examines the research theories underpinning the articles reviewed. Though 44% of the studies were without any identified theory, dynamic capabilities (DC) dominated the count with 14, representing 16%, the resource-based view (RBV) recorded nine articles to represent 10%. Socio-technical theory, systematic review models, organization information processing theory, and new theories conceptualized or developed by authors recorded three articles each, representing 3.4%.

Table 1. Distribution by Theory (> a paper)

Adopted Theories	Frequency	%
Dynamic capabilities (DC)	14	16
Socio-technical theory	3	3.4
Systematic literature review	8	3.4
Resource-based view (RBV)	12	10
Technological, organizational, and environmental framework (TOE)	2	2.2
Author's theory	3	3.4
Organization information processing theory	3	3.4
No theory	30	44.3

Theories such as technology, organizational, and environmental (TOE) recorded two articles, representing 2.2%. Adaptive capabilities, affordance theory, absorptive capacity, contingency theory, acceptance theory, organizational design theory, task-technology fit theory, technology acceptance model (TAM), cognitive capability, current learning theory, and organizational motivation theory each appeared once in the study (see Table. 1).

3.4 Trending Issues

Figure 3 depicts the issues embedded in the adopted themes and displays the trend in the research area from 2013 to 2017. Out of the human, technical and organizational capabilities, the authors identified issues bordering on BD integration strategies, BD economic impacts,

informational benefits of BDA, BD frameworks, BD socio-technical implications, BD quality constraints, analytics as a service, BD typology, constraints in BD decisions, challenges in interpreting BD output, BDA value creation models, ethical concerns, performance theories, performance frameworks, Big data integration challenges, and process innovation.

It was further discovered that for each issue addressed in a reviewed paper, the authors prescribed one or two useful use-case questions that seek to resolve either a technical, business or social issue or a bottleneck in the implementation stage of the BDA initiative. These use-case questions were collated and themed according to the IT/IS resource capabilities classification of "human, technology, and organizational capabilities" (Ross et al. 1996) with specific constructs to form an evaluation scorecard, as shown in appendix 1.
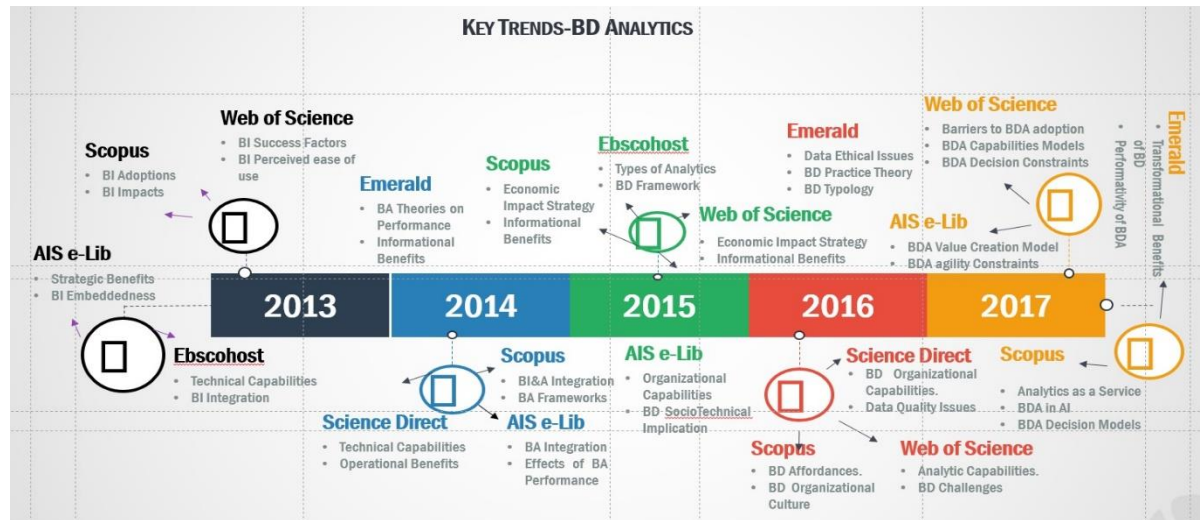

Fig. 3. The Issue Trend

3.5 Firm Evaluation Score Card

Both industry and academia often device means of measuring performance and feedbacks on actions borne out of strategic initiatives. For instance, while Ban et al. (2016) designed the first nationwide ProPublica surgeon scorecard to measure complication rates, Tan, Zhang, and Khodaverdi (2016) applied their performance scorecard in measuring client feedback in the automotive service industry. Similarly, the Sohar University in Oman established a strong association between the implementation of a strategic road map and a performance scorecard. Literature makes a case for low expected BDA investment benefits and performance for legacy firms (Bughin et al., 2017). Leading to the need to aggregate from literature, a criterion that can guide firms in evaluating their BDA projects and broaden their socio-technical understanding, requirements, and capabilities for BDA. The BDA Competence / Evaluation Scorecard (Appendix 1) got designed to assist firms that are considering partial to full analytical migration to track, monitor, and evaluate operational, tactical, and strategic decisions. The respective dimensions on the scorecard were further stratified into constructs and rated based on the score assigned and to a particular chosen answer to a question. The formula for rating a firm's total analytic competency stage is as follows:

$$\frac{\Sigma(s)}{\Sigma(x)}(100\%)$$

The summation of a firm's score on each competence criterion is $\Sigma(s)$, while $\Sigma(x)$ is the sum of all the default maximum scores of the framework. The scorecard framework is tied to the Davenport and Harris (2007) analytical maturity model to aid firms in situating their performance scores in the analytical maturity model's growth stages. The growth stages are categorized as follows: 90%–100% score is Stage #5 (Analytical Competitors), 89%–80% is Stage #4 (Analytical Company), 79%–70% is Stage #3 (Analytical Aspirations), 69%–60% is

Stage #2 (Localized Analytics), and 59% or less is Stage #1 (Analytically Impaired) (Table 2).

For example, based on Davenport and Harris (2007) analytical maturity model, every firm that seeks to compete on analytics, must aspire to reach "Stage 5" of maturity, where the search for new data and metrics are endless with essential analytical resources managed centrally and enterprise-wide. The leadership of this firm must have a strong passion for competing and supporting the firm's distinctive capabilities and strategy with analytics while engaging or training amateur analysts to world-class professionals. However, before "stage 5", firms can establish their maturity stage by using the BD evaluation scorecard, which is in the form of a five (5) Likert scale questionnaire. Each box ticked as an applicable gets assigned to the scale number, these scale numbers are summed up representing $\Sigma(s)$, which is further divided by the sum of all default maximum scores of the framework $\Sigma(x)$. A percentage of this value is compared to the score range of the maturity model to establish the firm's stage.

ANALYTIC MATURITY MODEL					
	DATA	**ENTERPRISE**	**LEADERSHIP**	**TARGETS**	**ANALYSTS**
STAGE 5 Analytical Competitors	The relentless search for new data and metrics	All key analytical resources centrally managed	Strong leadership passion for analytical competition	Analytics support the firm's distinctive capability and strategy	World-class professional analysts and attention to analytical amateurs
STAGE 4 Analytical Companies	Integrated, accurate, common data in a central warehouse	Critical data, technology, and analysts are centralized or networked	Leadership support for analytical competence	Analytical activity centered on a few key domains	Highly capable analysts in central or networked organization
STAGE 3 Analytical Aspirations	Organization beginning to create a centralized data repository	Early stages of an enterprise-wide approach	Leaders beginning to recognize the importance of analytics	Analytical efforts coalescing behind a small set of targets	The influx of analysts in key target areas
STAGE 2 Localized Analytics	Data usable, but in functional or process silos	Islands of data, technology, and expertise	Only at the function or process level	Multiple disconnected targets that may not be strategically important	Isolated pockets of analysts with no communication
STAGE 1 Analytically Impaired	Inconsistent, poor quality, poorly organized	N/A	No awareness or interest	N/A	Few skills, and these attached to specific functions

Table 2. Analytics Maturity Model (Source: Davenport and Harris 2007)

4. Discussion and Future Research Gap

This section discusses the results presented in the earlier section. From the results, we can posit that BDA drives operational insight for actionable decisions with some level of certainty in the artifacts outputs, which is something highly sought after in every business decision (Davenport, Barth, & Bean, 2012). Within the information systems discipline, the interest in and attention on BDA is evident in the number of research articles received even in the queried repositories. In the early stages of BDA, as evidenced in Figure 1 and Figure 3., the interest and expectations were very high with issues such as factors affecting adoption (Mahrt & Scharkow, 2013), adoption and impacts of social media analytics on businesses (Esteves & Curto, 2013) were identified. Other scholars noticed the strategic benefits of aggregating and linking heterogeneous data (Mithas, Lee, Earley, Murugesan, & Djavanshir, 2013) and frameworks for understanding enterprise analytic success factors (Mungree et al., 2013). Finally, agility through new technology (Demirkan & Delen, 2013; LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2013) and latency between data acquisition and decision (Leonardi, 2013) got researched to reflect the issues inhibiting firm's BDA capital investments drive.

Though accounts of some waning interest and unmet expectations borne out of the difficulties

encountered by early adopters (Bughin et al., 2017), the issues dealt with by researchers from 2014 to 2016 were somewhat an extension of those encountered by early adopters— specifically, data integration challenges affecting decision quality (Abawajy, 2015; Amankwah-Amoah, 2016), lack of frameworks and theories for policy, legal, regulatory, and performance concerns linked to business value (Amankwah-Amoah, 2015; Gandomi & Haider, 2015; Simonet, Fedak, & Ripeanu, 2015; Zhang, Hu, Xie, Zhang, Su, & Liu, 2015) were addressed. Most of these researchers also examined the impact of economic strategy on culture, analytic investment, agility, performance, and value realization (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016; Dobrev & Hart, 2015; Marshall, Mueck, & Shockley, 2015). Finally, socio-technical complexities in ethical and data quality concerns got identified as issues that might have caused the waning of interest and expectations of early adopters (Metcalf & Crawford, 2016).

Though Figure 1. Showed a trend of rising interest and expectations in 2017, as evidenced by the number of publications in all the six repositories, the issues were not distinctively different from the issues encountered in the years 2014 to 2016. The research community addressed issues such as adoption barriers, value-creating models, agility constraints, BDA decision constraints, Decision models, BDA as a service, and its associated transformational benefits. Based on the apparent rising trend in terms of volumes (Fig.1) and the sensitivity of issues depicted in Fig. 3, we predict a rise in interest and expectations (high number of research publications) of BDA in enterprise-wide business processes to continue. Generally, the issues examined yearly in the various repositories addressed technological, human, or organizational capability challenges inimical to BDA value creation and performance benefits. However, further studies should be encouraged to view capabilities from socio-technical or socio-material perspectives with broader scope and depth to Big data strategy, adoption, implementation, and practice. The imbrication of the technical, human, and organizational capabilities should minimize the challenges associated with poor data-driven culture (Kiron et al., 2014), data integration and ethics (Bialobrzeski, Ried & Dabrock, 2012), data quality (Bose, 2009), and process innovation bottlenecks that are common with legacy firms.

We further suggest that legacy firms adopt well-defined data management policies, goals, and strategies (McAfee & Brynjolfsson, 2012) to inform deliberate, analytical skill development policies for personnel and executives of business processes (Chang, Kauffman, & Kwon, 2014). Junior scholars should take a keen interest in critiquing new concepts, theories, and methodologies that seek to explain how to overcome concerns such as data ethics, data quality, data privacy, and data security. These challenges pose the most significant obstacle to realizing the fundamental socio-economic viabilities of BD initiatives (Nelson, Todd, & Wixom, 2005).

In analyzing the theory results, an interesting skewed trend was observed. Though 44.3% of the studies were not informed by any specific theory (Cervone, 2016; Janssen, Van Der Voort, & Wahyudi, 2017), most studies relied on dynamic capabilities (DC) theory (16%) and the resource-based view (RBV) (10%) to best explain and inform their inquiries. It is worth noting that dominant theories, such as Socio-Technical Theory, Organization Information Processing Theory, and Technology Organizational and Environmental (TOE) theory, appeared only once in the 88 papers reviewed. While some of these theories were combined to optimize outcomes, this study directs future research efforts in the knowledge generation process to dominant theories different from the list in Table 1 for different insight on the subject.

Besides the establishment of a firms' maturity stage, the objective answers to the developed evaluation scorecard in appendix 1 will further assist firms in identifying implementations

gaps regarding the scores in individual dimension and their corresponding constructs. Where areas or questions of lower scores can get the attention of leadership for the needed interventions for higher scores, which progresses the firm closer to the stage (5) of the maturity framework.

5. Conclusions

This study sieved through six well-known repositories for peered-reviewed studies on Big Data analytics in business processes published within the year 2013 to 2017. The sieving criteria resulted in 88 articles that got analyzed for the conceptual approach, research methodology adopted, and thematic issues identified. The study also enacted out of the 88 articles an analytical scorecard to assist business executives in evaluating progress and tracking the performance status of their firm's analytic journey for gaps. The study affirms that legacy firms with an improved socio-technical approach to addressing data quality constraints, data privacy complexities, ethical and security concerns could increase their propensity to generate expected benefits (Davenport, Barth & Bean, 2012). The findings further identify relevant gaps in theory, issues, context, and methodology. Combined with the scorecard, these identified gaps should benefit scholars in situating future research direction and practitioners in their attempts to embed big data analytics in business processes, evaluate BD implementation for competitive advantage. We posit further that BDA's infusion into business processes must take into account the formulation and enforcement of cultural and formalized data-driven process strategies that enable constant monitoring and reconstruction of operational processes.

Several limitations have been identified in the study, regardless of the adopted methodology. The study's result is likely not to reflect the exact trend since the study was limited to the English language, spans from 2013 to 2017, and did not also cover all repositories. That led to the exclusion of equally relevant articles in other languages, repositories, and years. The scorecard yet to be tested; therefore, future works can apply the scorecard framework to establish its reliability for purpose. This study will benefit the efforts of a broad range of researchers and practitioners. The findings will assist researchers in identifying new research questions and gain an overview of current research directions that align with their work. Practitioners will gain insight into challenges associated with integrating data, whether "big" or otherwise, into business processes and use the evaluation scorecards to track and evaluate their BD implementation and operations. Young scholars may use these findings as a guide to locate and publish various types of related articles and to gain further insight into the emerging field of advanced analytics.

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Appendix 1

BIG DATA ANALYTIC COMPETENCE AND EVALUATION SCORECARD

Kindly indicate the extent to which each of these statements describes your firm's Big data dimension and the corresponding construct, using a scale of 1–5, where **1=Not at all**, **2=To a small extent**, **3=To a moderate extent**, **4=To a large extent**, and **5=To a very large extent.**

DIMENSIONS	CONSTRUCTS	DETAILS	1	2	3	4	5
BDA Infrastructure [Janssen et al. 2017; Motamarri et al. 2017; Sayarajah et al. 2017; Vera-Baquero et al. 2015; Wang et al. 2016]	Connectivity	1. Our firm's analytics system is very reliable.	1	2	3	4	5
		2. Accessing appropriate data sources to produce and manage big data is possible (data can be accessed).	1	2	3	4	5
		3. Analytic insight is centrally shared with all remote branches.	1	2	3	4	5
		4. We utilize an open system network to boost analytic connectivity.	1	2	3	4	5
		5. There are identifiable communication bottlenecks when sharing analytical insights.	1	2	3	4	5
	Compatibility	1. Applications can easily be exported and used on multiple platforms (not platform dependent).	1	2	3	4	5
		2. Existing IT platform/architecture may make it easy to migrate to and measure big data analytics.	1	2	3	4	5
		3. The user interface links to access all platforms and applications seamlessly.	1	2	3	4	5
		4. Analytic-driven information is shared irrespective of location.	1	2	3	4	5
		5. External end-user access to our analytic interface from multiple points is possible.	1	2	3	4	5
	Modularity	1. Our analytic applications are reusable modules.	1	2	3	4	5
		2. We adopt object-oriented tools in creating our own or sourced analytic applications.	1	2	3	4	5
		3. Applications are adaptable to new needs and tasks.	1	2	3	4	5
		4. Object-oriented modules reduce new analytic development time.	1	2	3	4	5
BDA Strategy Alignment. [Akter et al. 2016; Cervone, 2016; Chongwatpol, 2016; Edgeman, 2013; Guo et al. 2017; Holsapple et al. 2014; Marshall et al. 2015; Pape, 2016; Pisano, 2017]		1. The big data analytics plan aligns with the company's mission, goals, objectives, and strategies.	1	2	3	4	5
		2. The big data analytics plan contains quantified goals and objectives.	1	2	3	4	5
		3. There is an availability of appropriate data to support analytics (the data exists).	1	2	3	4	5
		4. Data and analytics are taken seriously enough by the leaders at a strategic level in the business.	1	2	3	4	5
		5. Data is stored securely, only available to intended recipients, and is anonymized as needed.	1	2	3	4	5
		6. The big data analytics plan contains specific action plans/strategies that support company direction.	1	2	3	4	5
		7. We prioritize significant Big data analytics investments by the expected impact on business performance.	1	2	3	4	5
BDA Human Competency [Akter et al. 2016; Brock, 2017; Demirkan et al. 2015; Gunther et al. 2017; Wamba et al. 2017]	Technical Knowledge	1. The analytical team includes top programmers.	1	2	3	4	5
		2. Data quality aspects, such as data accuracy, definition, consistency, segmentation, and timeliness, are assured.	1	2	3	4	5
		3. The analytical team understands and manages project life cycles.	1	2	3	4	5
		4. The analytical team includes experts in data management.	1	2	3	4	5
		5. The analytical team includes experts in network management.	1	2	3	4	5
		6. The analytical team includes experts in system administration.	1	2	3	4	5
		7. The analytical team develops reliable Big data-driven decision support systems.	1	2	3	4	5
	Technical Agility	1. The analytical team demonstrates a superior understanding of technology trends.	1	2	3	4	5
		2. The firm has effective ways (systems) for storing and managing large volumes of data.	1	2	3	4	5
		3. With the firm, there is the ability to display and visualize the data to communicate insights.	1	2	3	4	5
		4. The analytical team demonstrates a superior ability to learn new technologies.	1	2	3	4	5
		5. The analytical team understands our firm's critical success factors.	1	2	3	4	5
		6. The analytical team acknowledges the dynamic enabling role of BDA.	1	2	3	4	5
	Business Astuteness	1. Our analytics team assimilates the firm's strategic plans and policies.	1	2	3	4	5
		2. Our analytics personnel is capable of interpreting business problems and developing appropriate technical solutions.	1	2	3	4	5
		3. Our analytics personnel is very knowledgeable about business functions.	1	2	3	4	5
		4. Our analytics personnel is very knowledgeable about the business environment.	1	2	3	4	5
	Relational Skills	1. Our analytics personnel is competent in terms of planning, organizing, and leading projects.	1	2	3	4	5
		2. Our analytics personnel are competent in terms of planning and executing work in a corporate environment.	1	2	3	4	5
		3. Our analytics personnel is competent in terms of teaching others.	1	2	3	4	5
BDA Management Tenets [Bumblauskas, Nold, Bumblauskas & Igou, 2017; Cao & Duan 2017; Hazen, Skipper, Ezell & Boone, 2016; Khan & Vorley, 2017; Laux, Seliger & Springer, 2017; Mawed & Aal-Hajj, 2017; Pauleen, 2017; Rothberg & Erickson, 2017; Sivarajah, Kamal, Irani, & Weerakkody, 2017]		4. Our analytics personnel work closely with customers and maintain productive user/client relationships.	1	2	3	4	5
	BDA Planning	1. We frequently adjust big data analytics plans to better adapt to changing conditions.	1	2	3	4	5
		2. We perform Big data analytics planning processes in systematic and formalized ways.	1	2	3	4	5
		3. We continuously examine innovative opportunities for the strategic use of big data analytics.	1	2	3	4	5
		4. We enforce adequate plans for the introduction and utilization of big data analytics.	1	2	3	4	5
	BDA Investment Decisions	1. When we create big data analytics, we estimate the effect they will have on the productivity of the employees' work.	1	2	3	4	5
		2. In analytics investment decisions, we consider how much these options will help end-users make timely decisions.	1	2	3	4	5
		3. We can secure the investment needed to build big data and analytics (infrastructure, skill, and training).	1	2	3	4	5
		4. When making big data analytics investment decisions, we think about and estimate the cost of training for end-users.	1	2	3	4	5
		5. In data analytics investment decisions, we estimate the time managers will need to spend overseeing changes.	1	2	3	4	5
	BDA Coordination	1. In our organization, business analysts and line people coordinate their efforts harmoniously.	1	2	3	4	5
		2. There are buy-in and engagement around the benefits of big data, and barriers to change can be overcome.	1	2	3	4	5
		3. Our business analysts and line people from various departments frequently attend cross-functional meetings.	1	2	3	4	5
		4. We share information widely for business analysts and job performers to make decisions based on available know-how.	1	2	3	4	5
		5. Our business analysts and line people frequently meet to discuss essential issues, both formally and informally.	1	2	3	4	5
	BDA Control	1. We are confident that Big data analytics project proposals are appropriately appraised.	1	2	3	4	5
		2. There is no challenge in defining the scope of big data projects in the firm.	1	2	3	4	5
		3. We can develop critical indicators for big data and analytics performance reporting.	1	2	3	4	5
		4. We ethically use the data and ensure all areas of the firm are using it acceptably.	1	2	3	4	5
		5. In our organization, the responsibility for Big data analytics development is clear.	1	2	3	4	5
		6. We continuously monitor the performance of the Big data analytics function.	1	2	3	4	5
		7. Our analytics department is clear about its performance criteria and privacy policy.	1	2	3	4	5
Process-oriented dynamic capabilities [Braganza, Brooks, Nepelski, Ali & Moro, 2017; Wamba et al. 2017]		1. Our company is better than competitors at connecting (e.g., information sharing) with parties within a business process.	1	2	3	4	5
		2. Our company is better than competitors at reducing costs within a business process.	1	2	3	4	5
		3. We manage the complexity of Big data processes (e.g., generating, storing, cleaning data, and producing analytics).	1	2	3	4	5
		4. Our company is better than competitors at bringing sophisticated analytical methods to bear on a business process.	1	2	3	4	5
		5. Our company is better than competitors at bringing detailed information into a business process.	1	2	3	4	5
Value [Akter et al. 2016; Côrte-Real, Oliveira, & Ruivo, 2017; Dobrev & Hart, 2015; Hartmann, Zaki, Feldmann & Neely, 2016; Ram, Zhang & Koronios, 2016; Schläfke, Silvi, & Möller, 2013; Seddon, Constantinidis, Tamm, & Dod, 2017; Trieu, 2017; Vera-Baquero, Palacios, Stantchev & Molloy, 2015]	Process Efficiency Benefits	1. We have improved business process efficiency.	1	2	3	4	5
		2. We have increased personnel productivity.	1	2	3	4	5
		3. We have improved the cost of effective decision making.	1	2	3	4	5
		4. We have reduced operational costs.	1	2	3	4	5
	Customer Intelligence Benefits	1. We have reduced marketing costs.	1	2	3	4	5
		2. We have reduced the time to market products/services.	1	2	3	4	5
		3. We have reduced customer return handling costs.	1	2	3	4	5
		4. We have increased responsiveness to/from suppliers.	1	2	3	4	5
		5. We have increased inventory turnover.	1	2	3	4	5
		6. We have reduced the loss of sales/loss services provided.	1	2	3	4	5
		7. We have reduced inventory levels.	1	2	3	4	5
		8. We have increased the geographic distribution of sales/services provided.	1	2	3	4	5
		9. We have increased the revenues/services provided.	1	2	3	4	5
		10. We have reduced the costs of transactions with business partners/suppliers.	1	2	3	4	5
		11. We have increased the efficiency of utilizing assets.	1	2	3	4	5
		12. We have improved competitive advantage.	1	2	3	4	5
		13. We have an increased return on investment (ROI).	1	2	3	4	5