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Big data-driven supply chain performance measurement system: a review and framework for implementation

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Performance measures and metrics (PMM) is identified to be an essential aspect of managing diverse supply chains. The PMM improves the firm's performance by providing open and transparent communication between the various stakeholders of an organisation. The literature suggests that big data analytics has a positive impact on the supply chain and firm performance. Presently, the literature lack studies that recognise the PMM relevant to big data-driven supply chain (BDDSC). The present study is based on a comprehensive review of 66 papers published with the primary objective to identify the various PMMs used to evaluate the BDDSC. The findings suggest that the PMMs applicable to BDDSC can be classified into two non-mutually exclusive categories. The first category represents 24 performance measures used to evaluate the performance of the big data analytics capability and the second category represents 130 measures used for assessing the performance of BDDSC processes. The study also reports the emergence of new performance measures based on increasing use of predictive and social analytics in BDDSC. Based on the results of the study a framework on BDDSC performance measurement system is proposed which will guide the managers to have a robust performance measurement system in their organisation.

Keywords: big data; supply chain management; performance measures; predictive analytics; data analytics

1. Introduction

Performance measurement is defined as the process of quantifying the efficiency and effectiveness of action. The set of metrics used to quantify the efficiency and efficacy of action is referred to as a performance measure (Neely, Gregory, and Platts 1995). The fundamental questions used to analyse the performance management systems are 'What performance measures are used? What are they used for? How much do they cost? And what benefit do they provide' (Neely, Gregory, and Platts 1995). Performance measures are believed to facilitate more open and transparent communication between the stakeholders of an organisation, leading to a supportive work environment and hence improved organisational performance (Gunasekaran and Kobu 2007).

Big data analytics (BDA) defined as collection of data, analytical tools, computer algorithms and techniques to derive meaningful insights, patterns from the collected large data sets (Jeble et al. 2018; LaValle et al. 2011) is gaining wide acceptance in the supply chain (SC) helping the managers to deliver sustainable value, improved business performance and competitive advantage (Wamba et al. 2017). Manyika et al. (2011) point out that BDA may lead to a new movement of productive growth by transforming economies. BDA is enabling novel ways of organising and analysing SC processes to drive SC performance (Hazen et al. 2016; Waller and Fawcett 2013), create manufacturing capabilities and improve customer satisfaction (Anwar, Khan, and Shah 2018). Studies have also found that the BDA has a positive influence on the firm performance (Gunasekaran et al. 2017; Wamba et al. 2017), building competitive advantage (Chen, Preston, and Swink 2015) through cost reduction, improved decisions, and improvements in products and services (Matthias et al. 2017). The supply chains adopting the BDA are referred to as big data-driven supply chains (BDDSC).

There have been numerous attempts in the SC literature to collate the performance measures and metrics (PMM) used for evaluating the SC performance. The PMMs are classified based on multiple dimensions that include; qualitative or quantitative (Beamon 1999; Shepherd and Günter 2006); cost and non-cost (Gunasekaran, Patel, and Tirtiroglu 2001); quality, cost, delivery, flexibility, strategic, operational, tactical (Gunasekaran, Patel, and Tirtiroglu 2001; Shepherd and Günter 2006); cost, quality, resource utilisation, flexibility, visibility, trust and innovativeness (Chan 2003); and the SC process using SCOR framework (Lockamy and McCormack 2004; Shepherd and Günter 2006). The previous studies argue

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that design, development, and implementation of PMMs is not a one-time activity and has to be continuously monitored and reviewed for accommodating the changes in the competitive environment (Beamon 1999; Bourne et al. 2000; Medori and Steeple 2000).

The PMMs used in traditional SC is based on historical information, isolated, static and are less efficient in delivering information to the decision makers (Lapide 2010). The traditional performance measurement system (PMS) is concerned to find what happened in the past and the reasons for the same and therefore, may not apply to manage the BDDSC performance which is fast-changing, highly volatile and are expected to be highly proactive, anticipating future performance instead of reacting to the problems after they occur (Stefanovic 2015). It would be interesting to find whether the PMM of BDDSC complements the PMM used in the traditional SC and does it provide additional information on what will happen in the future, helping the decision makers to take corrective actions to prevent the occurrence (Bauer 2005). To the best of our knowledge, no studies have explored the literature and collated the PMM considered in a BDDSC. It is necessary to understand how the PMM used in BDDSC PMS are different from the traditional SC PMM. This knowledge will help the performance managers to design, implement and monitor an active BDDSC PMS. The above reasons motivated the researchers to conduct this study to explore and comprehend the PMM used to evaluate the BDDSC performance and propose a PMS. The study investigates how the BDA capability in a supply chain is conceptualised, what measures contribute to the development of a strong BDA and how these measures complement the existing PMM used in traditional SC. We used a systematic literature review suggested by Tranfield, Denyer, and Smart (2003) to seek information for the following research questions (RQs);

RQ1: How is BDA conceptualized in a BDDSC?

RQ2: What PMM are used to evaluate BDDSC performance?

RQ3: How to implement a BDDSC PMS?

The study contributes to the SC management literature by identifying a set of PMM that can be used by the organisations to evaluate their BDDSC performance. Based on the findings of the study, we also propose a BDDSC-PMS framework which will guide the managers to implement PMS in their organisations.

The remaining of the paper is organised as follows: Section 2 provides background on PMM in traditional SC and need for PMM in BDDSC. Section 3 presents the review methodology. The findings of the study are presented in section 4. Section 5 discusses the BDDSC –PMS framework based on the results of the review. Section 6 offers managerial implications and future research directions. Section 7 presents the conclusions drawn from the study.

2. Performance measures in traditional and big data-driven supply chains

Performance management plays a significant role in the successful functioning of an organisation. The timely and efficient evaluation of the SC helps in strategy formulation, implementation, and monitoring. The PMMs have undergone a considerable transformation from a very traditional PMM to advanced and balanced techniques (Mishra et al. 2018). Kaplan and Norton (1992) proposed the use of a balanced scorecard approach that suggests the use of financial and non-financial measures to achieve strategic alignment. The primary objective of the balanced scorecard approach was to provide managers with better decision-making environment that included a broader perspective of both tangible and intangible assets. A significant contribution is in the form of SC operation reference (SCOR) framework that characterised those SC practices and processes which has a substantial influence on the SC performance. The various domains used for categorisation included plan, source, make, deliver and return. Many studies have provided PMM taxonomy based on a critical review of the literature. Shepherd and Günter (2006) identified that SC activities such as process modelling, data integration, software support, and forecasting did not receive much attention in the SC performance management literature. Arzu Akyuz and Erman Erkan (2010) also identified various aspects of PMM such as collaboration, agility, flexibility, and IT support systems that were not considered for SC performance evaluation. The other significant contribution was from Gunasekaran, Patel, and McGaughey (2004) in the form of a validated set of PMM.

Further, Gunasekaran and Kobu (2007) classified the various SC PMM using balanced scorecard, components of measures, location and nature of measures, traditional versus modern measures and decision levels. The review by Gopal and Thakkar (2012) identified considerable scope for research to address critical issues in SC PMM, benchmarking, integration, business intelligence, and collaborative decision-making. Lapide (2010) reports that the traditional SC PMM are based on historical data, which are static and reactive. There is a competitive pressure on the SCs to enable proactive evaluation and management (Bauer 2005).

In a BDDSC, the BDA capability is seen as a significant asset that helps the organisations to extract the hidden knowledge from the collected information (Viet, Behdani, and Bloemhof 2018). Stefanovic (2015) identified that BDDSC-PMS should provide the following benefits to the organisations, resulting in strong BDA capability and improved SC performance.

(i) New knowledge for improved future projections on performance.
(ii) A standardised approach to SC performance measurement across all the levels in SC hierarchy.
(iii) Knowledge-based planning and strategy development.
(iv) Organisations ability to develop proactive SC strategies.
(v) Improved competitive advantage on the dimensions of better adaptability, reduced SC risk and improved responsiveness.
(vi) The collaborative and persistent performance monitoring system

These benefits inspired us to review the literature on BDDSC and explore the appropriate PMM to understand how a BDDSC- PMS can be effectively implemented to monitor the SC performance.

3. Review methodology

The information to the RQs was obtained through a systematic literature review, based on the guidelines suggested by Tranfield, Denyer, and Smart (2003). The review was conducted in three main stages that included; (i) Planning the review, (ii) Conducting the review and, (iii) Discussion on findings and knowledge dissemination. The review is discussed below.

3.1. Planning the review

The primary objective of this research was to identify relevant PMM for evaluating BDDSC performance. Therefore the SLR was designed to include the research papers that addressed the applications of BDA in SC management or established the linkage of BDA with SC performance. Papers that did not cover these aspects or were outside the scope of RQs were not considered for review. The procedure adopted for selection of the papers is discussed in the next stage.

3.2. Conducting the review

The present study is based on the research papers extracted from Scopus database, as it covers a superior number of journals as compared to other leading online databases (Chadegani, Salehi, and Yunus 2013; Mishra et al. 2018). To ensure data consistency and relevance across the selected papers the selection of the search keywords were guided by the objectives of the study and included ‘big data’, or ‘data mining’, or ‘data analytics’, or ‘data-driven’, or ‘predictive analytics’, or ‘supply chain analytics’ AND ‘supply chain performance’, or ‘firm performance’, or ‘organizational performance’, or ‘business performance’ or ‘performance measures’ or ‘performance metrics’. Initial search with the use of the above combination of keywords in the title, abstract, and keyword index resulted in a total of 1453 papers. In the second stage, we restricted the articles to those published in journals up to the year 2018, excluding the articles those published in conference proceedings, book chapters, doctoral work, white papers, editorial columns, etc. reducing the total count of papers to 587. The number of papers were further reduced to 95 by limiting the search to the subject area ‘Business, Management, and Accounting.’ The authors read the introduction and conclusion/discussion section of each paper and removed the papers not aligning with the review objectives, were highly technical or did not address the selected keywords. Total sixty-six (66) research papers were retained for the final review. The list of journals selected for the study is presented in Appendix A.

3.3. Reporting of findings and knowledge dissemination

The results of the review are presented in this stage of the systematic literature review. The findings of the present study are detailed in a narrative form, giving the contents of what has been written on a topic or a subject. The review findings are discussed in the next section.

4. Review findings

4.1. Theories for BDA conceptualisation and its impact on BDDSC performance

A BDDSC- PMS should have the capability to collect, integrate, consolidate big data, and apply BDA tools to extract valuable insights from the hidden trends and patterns in big data. The findings from the review suggest that to study the impact

Table 1. Different theories used to study the impact of BDA on BDDSC performance.

Theories	Key references
Resource-based view	Chae, Olson, and Sheu (2014a), Chae et al. (2014b), Gupta and George (2016), Barbosa et al. (2017), Hazen et al. (2016), Tan et al. (2015), Waller and Fawcett (2013), Gunasekaran et al. (2017), Popovič et al. (2018), Müller, Fay, and vom Brocke (2018), Chavez et al. (2017) Akter et al. (2016).
Knowledge-based view	Akter et al. (2016), Chae et al. (2013), Chae, Olson, and Sheu (2014a), Chae et al. (2014b), Ji-fan Ren et al. (2017), Raguseo and Vitari (2018), Hazen et al. (2016).
T-O-E framework	Wamba et al. (2015), Chen, Preston, and Swink (2015), Tan et al. (2015)
Dynamic capability theory	Chae and Olson (2013), Richey et al. (2016), Chen, Preston, and Swink (2015).
Scpm3	de Oliveira, McCormack, and Trkman (2012)
Organisational information processing theory	Zhu et al. (2018), Chen, Preston, and Swink (2015), Srinivasan and Swink (2018)
Information success theory	Ji-fan Ren et al. (2017), Wamba et al. (2016), Huang, Wang, and Huang (2018)

of BDA on the firm or SC performance, BDA is conceptualised using different theories and frameworks. These theories help us to understand the critical components of BDA capabilities required to achieve improved BDDSC performance. A summary of the theories used to study BDA in SCM is presented in Table 1.

4.1.1. Resource-based view

Resource-based view is a managerial framework used to determine the significant strategic resources that can be exploited by the organisations to achieve sustainable competitive advantage (Barney 1991). According to resource-based view, the resources that are readily available for all the firms and can be traded in the market are the ‘tangible’ resources, whereas the resources without any clear and visible boundaries are the ‘intangible’ resources (Barbosa et al. 2017; Gupta and George 2016). The transformation of the conventional SC systems to BDDSC creates new competitive advantages for the firm through improved operational effectiveness (Manyika et al. 2011). BDA is considered a significant organisational and technological resource provides useful information and knowledge leading to the development of adequate competencies (Tan et al. 2015; Waller and Fawcett 2013). BDA is a highly valuable, inimitable, and non-substitutable resource that combines data management, IT-based planning, and performance management resources (Chen, Preston, and Swink 2015; Schläfke, Silvi, and Möller 2013). BDA assimilation, which influences the SC performance is observed as a three-stage post-diffusion process lead by organisational resources and top management support (Gunasekaran et al. 2017). The BDA, an organisational resource is moderated by the firm’ s BDA capabilities and other organisational factors such as BDA strategy, top management support, financial resources, and people engagement Popovič et al. (2018). Jeble et al. (2018) argues that the resource-based view has a significant limitation of not identifying the conditions in which the firm’s resources or capabilities provide a competitive advantage. However, the econometric study conducted by Müller, Fay, and vom Brocke (2018) analyses the direction, sign, and magnitude of the relationship between BDA and firm performance based on objective measurements of BDA assets that included technological and human capabilities possessed by the organisations. They found that BDA investments in the BDA assets and the type of industry in which the company operates determines the impact of BDA on the firm’s performance improvement. Based on resource-based view, Chavez et al. (2017) investigated the linkages between the BDA, manufacturing capabilities, and customer satisfaction and found that BDA contributes positively to the various dimensions of manufacturing capability dimensions. Akter et al. (2016) combined the resource-based view with the entanglement view of socio-materialism and conceptualised BDA to consist of management, technology, and talent capability influencing the firm performance.

4.1.2. Knowledge-based view

The knowledge-based view perspective builds upon and extends the resource-based view of the firm. Although the resource-based view recognises the critical role of knowledge in firms in achieving a competitive advantage, the proponents of the knowledge-based view argue that the resource-based view perspective does not go far enough. In knowledge-based view**,** knowledge is considered the most strategically significant resource of a firm as it is usually difficult to imitate and socially involved. The studies by Akter et al. (2016), Chae, Olson, and Sheu (2014a), Chae et al. (2014b), Hazen et al. (2016), and Ji-fan Ren et al. (2017), conceptualised BDA on the knowledge-based view. BDA value is considered as a knowledge resource, and its impact on firm performance is found to be dependent on the data quality (Hazen et al. 2016). High-quality levels of data acquired by the firm enable strong BDA capability that are valuable, rare, imperfectly mobile, not imitable, and

Table 2. BDA capabilities and asset development.

Type of Assets	BDAC
Human assets	• Capacity to understand data • Expertise in handling IT systems/software and the use of data • Opinion plus data • Actionable results • Data visualisation skills • The ability for the contextual recommendation • Analysis paralysis • Dedicated Business Intelligence /Insights teams • New blood (leadership)
Technology Assets	• Significant investments • Buying other companies • Incompatibility among multiple IT platforms and matching up disparate systems • Legacy systems • Compiling Metadata • Creating ontologies/typologies • Investing in a third party help • Ability to access third-party data
Relationship assets	• External help to adapt and integrate • Strategic partners/suppliers of specialist services

not substitutable (VRINN). The firm that best acquires distributes and deploys their knowledge assets can create long-term performance advantages that might be transferred, absorbed, and applied for improving financial performance.

4.1.3. *Technology, organization and environment framework*

T-O-E framework explains the influence of the technological, the organisational, and the environmental context on the process of technology innovation adoptions by the firms (DePietro, Wiarda, and Fleischer 1990). The internal and external technologies (both equipment and procedures) are analysed in the technological context. The organisational context describes the characteristics (firm's size, the degree of centralisation, the degree of formalisation, managerial structure) and resources of the firm (human resources, amount of slack resources, and linkages among employees). The size and composition of the industry, the firm's competitors, the macroeconomic context, and the regulatory environment are included in the environmental context (DePietro, Wiarda, and Fleischer 1990). Business value is an outcome of how well a sound big data strategy is implemented (Wamba et al. 2015). Therefore, the organisations should examine the financial implications on enhancing the innovation and product design capabilities before BDA adoption in SCM (Tan et al. 2015; Wamba et al. 2015). Chen, Preston, and Swink (2015) used the T-O-E framework to study the inter-relationships with specific T-O-E elements and managerial factors, thus developing a complete model of organisational-level IT usage. The human assets, technology and relationship assets of the firm have a direct link to the firm performance (Ramanathan et al. 2017). In Table 2 we summarise the various BDA capabilities required to build these assets.

4.1.4. *Knowledge-based view*

Dynamic capability refers to the capability of the organisation to align with the available resource base (Teece, Pisano, and Shuen 1997). Dynamic capability is defined as 'the firm's ability to integrate, build and reconfigure internal and external competencies to address rapidly changing environments' (Chae and Olson 2013). The focus of the dynamic capability view is more on the issue of competitive survival in response to rapidly changing contemporary business conditions, rather than emphasising on the sustainable competitive advantage as in resource-based view. Dynamic capabilities are significant for the organisations as it supports them to create, modify, integrate, acquire, and discharge their resources. BDA is conceptualised to be a dynamic capability, a particular kind of organisational resource in BDDSC (Barbosa et al. 2017; Richey et al. 2016).

4.1.5. *SC performance management maturity model*

The SC performance management maturity model developed by de Oliveira, Ladeira, and McCormack (2009) comprises thirteen groups of hierarchically interrelated capabilities that are classified on five levels of maturity. The brief description of different levels is given in Table 3.

Table 3. Snapshot of SC performance management maturity model.

Level	Description
I (Foundation)	• Focused on building an underlying structure. • Planning, order management, fulfilment, and procurement are not the focus area.
II (Structure)	• Distribution and demand planning processes get structured
III (Vision)	• Planning, source, make, deliver are viewed distinctly • Focus on the development of cross-functional teams
IV (Integration)	• Firms focus on establishing long-term collaborative relationships with all their SC stakeholders. • Strategic planning team focus on selecting SC partners and building long-term relationships with suppliers and customers
V (Dynamics)	• SC attains a high level of integration • Firm's take control of demand and capacity constraints by establishing a pull system through the development of a close relationship with customers

Table 4. BDA investments in SC processes.

SC Maturity level	Investments needed in the following SCOR domains	Reasons
Level I	Plan, Source, and partly Make.	• Poorly defined (ad hoc) processes • Focus on planning operations on deciding on which resources to be exploited
Level II	Deliver	• Defined processes • Focus on fulfilling the orders of its customers.
Level III	Make	• Focus shifts on aligning make the process to supply high-value products and services to customers.
Level IV and V	Source	• Focus on cooperation and collaborations with customers and suppliers • Strategic partnership/alliances

Table 3 confirms that the SC performance management maturity model is a process-oriented model, with information as an essential driver for success. The process maturity in the SCs influences the information processing needs, which in turn affects the relationship between BDA and performance results (de Oliveira, McCormack, and Trkman 2012). de Oliveira, McCormack, and Trkman (2012) argued that the SC maturity level decides the information processing needs and capabilities of an organisation. Their study identifies the level of investments to be made for developing BDA capability in the different SCOR areas (see Table 4). BDA investments in the plan area are required to be kept minimum as BDA is meant to be used for executing the strategies in the source, make and deliver areas and not for planning purpose.

4.1.6. *Organisation information processing theory*

The organisational information processing theory states that the firm's information processing performance is an outcome of the information processing needs and the information processing capability possessed by the firm. Zhu et al. (2018) argues that uncertainties in the SC can affect the relationship between information processing capabilities and related outcomes (Chen, Preston, and Swink 2015; Wong, Potter, and Naim 2011). Therefore, it becomes essential for organisations to develop the capability to proactively engage in communication with stakeholders for improved visibility and traceability in SC operations. Zhu et al. (2018) used the organisational information processing theory within the SCOR framework to investigate the impact of BDA on the firm's information processing capabilities and SC processes. The organisational information processing theory was used by Srinivasan and Swink (2018) to study the influence of BDA on firm performance.

4.1.7. *Information success theory*

The IST is a comprehensive model that examines the information system success based on the relationship between six of the most critical dimensions of success viz., information quality, system quality, service quality, system use/usage intentions, user satisfaction, and net system benefits (DeLone and McLean 1992). BDA system quality that includes the concerns like adaptability, accessibility, response time, privacy and information quality play a significant role in deciding the business value; a firm might obtain from BDA deployment (Ji-fan Ren et al. 2017). Organisations with BDA implementations have better financial and market performance (Huang, Wang, and Huang 2018).

The above theories suggest that BDA provides improved SC visibility, transparency, and performance. It is necessary that organisations invest in developing their BDA capabilities. However, it is imperative that they evaluate their current BDA capability for better utilisation of their investment. We identify and collate twenty-five performance measures from the literature that may be used by the organisations to evaluate the effectiveness of their current BDA capability and plan for future improvements.

4.2. Performance measures and metrics for evaluation of BDA capability

Neely, Gregory, and Platts (1995) suggests that performance measurement is used for quantifying the efficiency and effectiveness of action and should consider the benefit they provide to the organisations. As BDA is conceptualised as a significant organisational resource having a positive influence on the SC and the firm performance, it is essential to have a quantified list of measures to evaluate the BDA capability. Table 5 presents a list of twenty-five performance measures classified on the dimension of cost versus non-cost and qualitative versus quantitative measures. The cost measures are related to the distribution costs of products, return on investment, information-processing, investments made on developing BDA capability, and the non cost measures are based on the dimensions of quality, time, flexibility, and innovativeness (De Toni and Tonchia 2001; Gunasekaran, Patel, and Tirtiroglu 2001; Gunasekaran and Kobu 2007). Both the cost and non-cost measures can be either qualitative or quantitative. For example, the data quality cannot be quantified regarding incremental influence it has on the firm's financial performance.

It is observed from Table 5 that 95 percent of the measures are non-cost based with only one measure (BDA investment) based on cost dimension. The majority (70 percent) of the non-cost based measures represented quality dimension, five measures the flexibility dimension and two measures the time dimension. None of the measures represented the innovativeness dimension. Eighty-three percent of the measures were qualitative. Further BDA contributes to all the dimensions of SC processes such as plan, source, make, deliver and return.

4.3. Performance measures used in big data-driven supply chain processes

The PMM presented in the above section relates to the measures used to develop the BDA capability. The literature suggests that the PMM in a BDDSC are fast-changing, highly volatile and are expected to be highly proactive, anticipating future performance instead of reacting to the problems after they occur as compared to a traditional SC, where the PMM is based on historical information that is isolated, static and are less efficient in delivering information to the decision makers (Lapide 2010). Therefore we reviewed selected papers to identify the PMM that are used to measure the BDDSC processes. The primary objective was to explore the new PMM that complements the existing list of PMM that are used in traditional SC. Table 6 presents a list of PMM that were identified from the review of selected papers. The PMM is classified using the SCOR framework in addition to the cost/non-cost and quantitative/qualitative dimensions used to classify the PMM for BDA capability. SCOR framework is one of the most rigorous SC performance evaluation and strategic decision-making tool when aligned with SC visibility strategy, help the organisations to achieve improved efficiency, measurable and actionable outcomes (Ntabe et al. 2015). The SCOR is structured around five key SC processes (*viz., plan, source, make, deliver, and return*) and all the information and physical flows are represented according to these domains (Huang, Sheoran, and Keskar 2005; Hwang, Lin, and Lyu 2008; Kasi 2005; SC Council 2008). A BDDSC analysed using a SCOR framework provides reliable and useful information to the decision makers on each domain and helps the organisation to plan their BDA investments in alignment with their performance objectives (Trkman et al. 2010). SCOR framework has been previously used in classifying the PMM and found to identify and rectify the performance problems persistent in respective SC processes (Gunasekaran, Patel, and Tirtiroglu 2001; Shephard and Günter 2006).

Table 6 presents a list of 130 performance measures identified from the BDDSC literature. These measures are arranged according to the SCOR framework and classified on the dimensions of cost/non-cost and qualitative/quantitative dimensions. The results indicated that most of the studies focused on developing the PMM for the plan process (44%) followed by make (23%), return (13%), deliver (15%) and source process (10%). The findings on what these performance measures intended to measure were found to be imbalanced with the quality measures receiving the highest representation (68%) followed by cost (28%), flexibility (13%), time (9%), and innovativeness (04%). Our findings deviate from the previous studies on traditional SC, where the cost-based measures were used to a high distinction (Beamon 1999; Shepherd and Günter 2006). However, the lack of measures on flexibility and innovativeness was in line with the findings of the previous studies. The summary statistics of performance measures are presented in Table 7.

Table 5. BDA Performance Measures.

BDAC performance measures	Definitions	Cost (C) Time (T) Quality (Q) Flexibility (F) Innovativeness (I)	Qualitative (QL) or Quantitative(QN)
BDA Investments	This includes the investments made on the technology, training human resources to develop BDAC.	C	QN
Accessibility	The extent to which the BDA platform is accessible to the decision makers.	F	QL
Adaptability	The extent to which the BDA platform can be adapted to meet various needs in changing situations.	F	QL
Compatibility	The compatibility of BDA technologies with existing systems.	F	QL
Integration	The capability to integrate the data from different formats such as audio, text, video, and images.	F	QL
Modularity	The flexibility offered by the BDA platform to add, modify, or remove features from, or to the model.	F	QL
Analytical tools skill-set	The user's knowledge of using appropriate analytical tools and techniques.	Q	QL
Business domain knowledge	The expert business knowledge and deep understanding the BDA users have on industry rules, regulations, policies, etc.	Q	QL
Connectivity	The connectivity between the various SC partners for data sourcing and sharing in real-time.	Q	QN
Control	The amount of control the firms have on their BDA department/team.	Q	QL
Co-ordination	The coordination between the analysts and the line managers in the decision-making process.	Q	QL
Data Currency	The perceptions of the user on how the latest is the data.		
Data accuracy	The perception of the user that all the information captured by the BDA system is highly accurate.	Q	QL
Data completeness	The perception of the user that the BDA system captures all the necessary information.	Q	QL
Data-driven culture	The use of BDA to manage all the SC processes.	Q	QL
Data format/consistency	The perception of the user on data format and its consistent use on different platforms.	Q	QL
Relational domain knowledge	The interpersonal skills and the ability to work closely with professionals from different functions	Q	QL
Reliability	The extent to which the BDA platform can be relied upon to be free from any form of disruption or interferences.	Q	QL
Security and Privacy	Data security and privacy at different stages of collection, storage, processing, and sharing.	Q	QL
Technical domain knowledge	The expert technical knowledge and deep understanding, the BDA users have on the various aspects of BDA technologies.	Q	QL
Top management commitment	The degree to which the top management understands supports and appreciates the BDA capabilities.	Q	QL
Volume of data	The ability of the BDA platform to collect, store, analyse and share a large size of data.	Q	QL
Real-time data	The capability of the BDA system to collect, analyse and share the information in real-time.	T	QN
Response time	The timeliness and promptness of the BDA platform to respond to any queries or requests.	T	QN

Further, the study identified a new set of performance measures that were not used in traditional supply chains. These measures are associated with the predictability of the occurrence of events in the different BDDSC processes and include predictability of machine failure, quality, maintenance requirements, procurement frauds, and customer expectations. The other set of new performance measures that compliments the performance measures used in the traditional SC are the customer-oriented measures in the return domain and includes the number of customer queries, reviews, ratings, etc.

The performance measures identified for the evaluation of BDA capability and BDDSC processes, as listed in Tables 5 and 6, may be used by the performance managers to evaluate their BDDSC. In the following section, we present a BDDSC PMS framework that will guide the performance managers to implement and monitor the PMS in their organisations.

5. Big data-driven supply chain performance measurement system (BDDSC-PMS)

The performance measures used to evaluate the SC processes in a BDDSC provide organisations with the ability to predict future performance. It is implied from the review that in a BDDSC the performance relies on strong BDA capability, compelling the organisations to develop strong BDA capabilities. BDA is conceptualised as a significant organisational resource, and therefore it needs to be utilised economically. The BDDSC-PMS framework, as shown in Figure 1 is conceptualised on the organisational information processing theory. According to this theory, the firm's information processing performance is based on information processing needs and information processing capability (Trieu 2017). We also felt it appropriate to extend the SCOR framework for the proposed BDDSC- PMS, as we already have a ready reference of performance measures classified on the dimensions of SCOR dimensions (see Table 6). The use of SCOR framework in BDDSC PMS will allow all the SC partners to communicate in a common language providing a standardised definition for processes, process elements, and metrics (Huang, Sheoran, and Keskar 2005). SCOR model is found to improve the SC efficiency offering measurable and attainable outcomes when aligned with the SC visible strategy (Ntabe et al. 2015). As shown in Figure 1 the BDDSC-PMS has three antecedents leading to the predictive performance management that are discussed below.

5.1. BDDSC performance planning

BDDSC performance planning, the first component of the BDDSC-PMS deals with identifying the information needs of the organisation. It is implied that the performance managers should identify their information requirements, aligned with the strategic objectives of the organisation. Once the information requirements are identified, the managers must define their priorities regarding financial (cost) and non-financial (time, quality, flexibility, and innovativeness) measures. These priorities should be assigned based on the extent to which these measures contribute to achieving the strategic objectives. Next, the manager is required to set performance targets on the selected measures (*refer Table 6 for selection of measures*). The selected measures could be quantitative and qualitative and should be able to translate the strategies into specific objectives. It is implied that the managers must have a thorough understanding of how the different SC processes influence the firm's objectives and accordingly set realistic performance targets. These performance targets are required to be communicated to all the functional managers and SC partners to guide their operational decisions. In this stage, the managers will also be

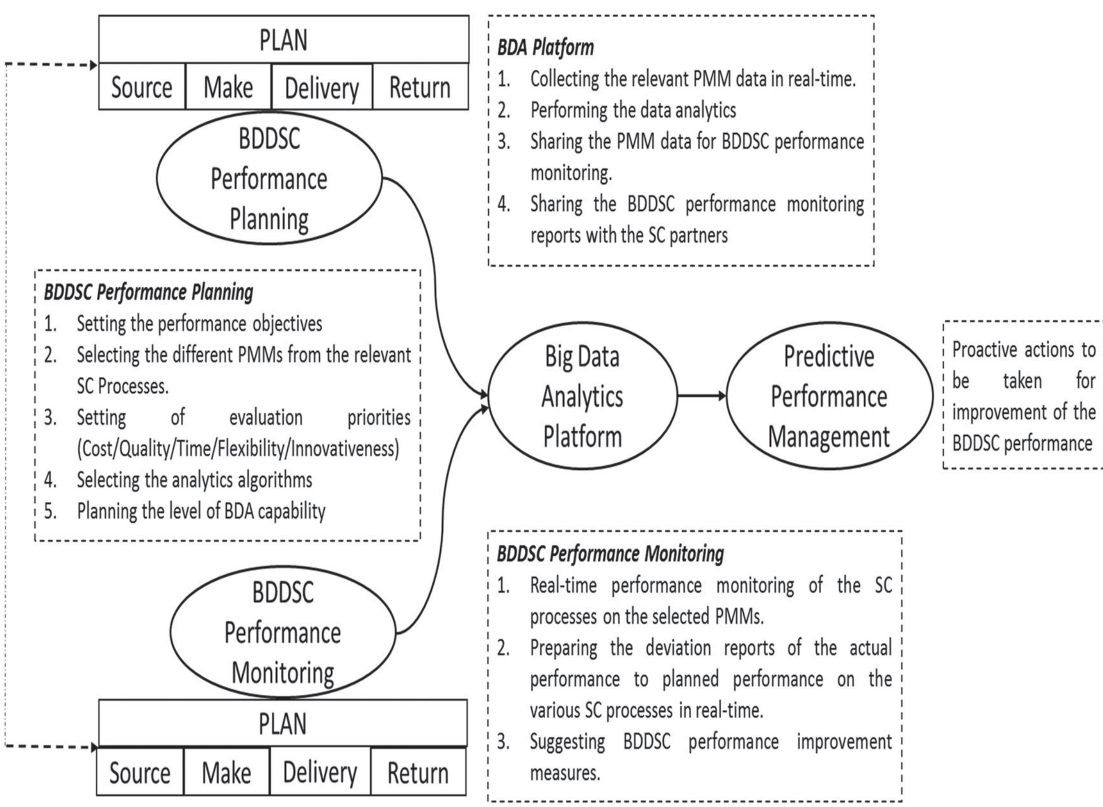

Figure 1. A framework for BDDSC performance measurement system.

Table 6. Performance measures for BDDSC processes.

BDDSC Process	Performance Measures	Cost (C) Time (T) Quality (Q) Flexibility (F) Innovativeness (I)	Qualitative (QL) Quantitative (QN)	Key References
Plan	Ability to learn new technology	I	QL	Fernando, Chidambaram, and Wahyuni-TD (2018)
	Accounts receivables	C	QN	Huang, Wang, and Huang (2018)
	Accounts receivable turnover	C	QN	Huang, Wang, and Huang (2018)
	Accurate demand forecasts	Q	QN	Fernando, Chidambaram, and Wahyuni-TD (2018)
	Asset utilisation	C	QN	Gunasekaran et al. (2018), Chen, Preston, and Swink (2015)
	Average year on year sales growth	C	QN	Chen, Preston, and Swink (2015)
	Buyers flexibility	F	QN	Hofmann (2017)
	Cash flow	C	QN	Anwar, Khan, and Shah (2018)
	Cash-to-cash cycle time	C	QN	Chen, Preston, and Swink (2015)
	Collaborative inventory planning	Q	QL	Stefanovic (2015)
	Cost reduction	C	QN	Chavez et al. (2017), Lee (2017), Zhan and Tan (2018)
	Decision-making lead times	T	QL	Hazen et al. (2016), Hofmann (2017), Richey et al. (2016)
	Demand shaping	Q	QN	Chae (2015)
	Direct control of the downstream inventory	Q	QL	Hofmann (2017)
	Employee satisfaction	Q	QL	Anwar, Khan, and Shah (2018)
	Environment support	Q	QN	Gunasekaran et al. (2018)
	Inter-departmental relations	Q	QL	Stefanovic (2015)
	Inventory cost	C	QN	Chavez et al. (2017), Kwon, Lee, and Shin (2014)
	Inventory turnover	C	QN	Chen, Preston, and Swink (2015)
	Labor expenses	C	QN	Huang, Wang, and Huang (2018)
	Labor productivity	C	QN	Huang, Wang, and Huang (2018)
	Low product price	C	QN	Srinivasan and Swink (2018)
	Market expansion	F	QN	Chen, Preston, and Swink (2015), Ren et al. 2017, Raguseo and Vitari (2018)
	Market sensing	Q	QN	Chae (2015)
	Market share	C	QN	Gunasekaran et al. (2018), Chen, Preston, and Swink (2015)
	Meeting customer demand	C	QN	Chen, Preston, and Swink (2015)
	New product development	F	QN	Matthias et al. (2017), Ji-fan Ren et al. 2017, Raguseo and Vitari (2018)
	New product development success rate	F	QN	Schoenherr and Swink (2015), Ji-fan Ren et al. (2017), Raguseo and Vitari (2018)
	New service propositions	F	QN	Matthias et al. (2017)
	Order flexibility	F	QN	Bock and Isik (2015)
	Order fulfilment	Q	QN	Chae, Olson, and Sheu (2014a), Chae et al. (2014b), Srinivasan and Swink (2018)
	Order fulfilment lead time	T	QN	Hofmann (2017), Srinivasan and Swink (2018)
	Order processing lead time	T	QN	Hofmann (2017), Srinivasan and Swink (2018)
	Order taking lead time	T	QN	Chavez et al. (2017), Srinivasan and Swink (2018)
	Overhead costs	C	QN	Chavez et al. (2017)
	Process innovation	I	QN	Fernando, Chidambaram, and Wahyuni-TD (2018), Krishnamoorthi and Mathew (2018), Gunasekaran et al. (2018), Tan et al. (2015)
	Product Innovation	I	QN	Tan (2018), Chae (2015), Tan et al. (2015), Zhan et al. (2017)

(*Continued*).

Table 6. Continued.

BDDSC Process	Performance Measures	Cost (C) Time (T) Quality (Q) Flexibility (F) Innovativeness (I)	Qualitative (QL) Quantitative (QN)	Key References
	Product mix flexibility	F	QN	Chae, Olson, and Sheu (2014a), Chae et al. (2014b)
	Profit	C	QN	Anwar, Khan, and Shah (2018), Gunasekaran et al. (2018), Zhan and Tan (2018), Akter et al. (2016), Wamba et al. (2017), Bag (2017), Gravili et al. (2018), Ji-fan Ren et al. (2017), Raguseo and Vitari (2018), Song et al. (2018), St-Pierre and Delisle (2006)
	Profit margin	C	QN	Huang, Wang, and Huang (2018)
	Quality of work	Q	QN	Chen, Preston, and Swink (2015)
	Reduced management planning costs	C	QN	Kwon, Lee, and Shin (2014)
	Reduced management planning time	T	QN	Kwon, Lee, and Shin (2014)
	Resource use and availability	C	QL	Fernando, Chidambaram, and Wahyuni-TD (2018)
	Return on asset (ROA)	C	QN	Anwar, Khan, and Shah (2018),
	Return on human resources	C	QN	Huang, Wang, and Huang (2018), Gunasekaran et al. (2018), Gravili et al. (2018)
	Return on Equity (ROE)	C	QN	Huang, Wang, and Huang (2018)
	Return on investment (ROI)	C	QN	Akter et al. (2016), Wamba et al. (2017), Gravili et al. (2018)
	Revenue	C	QN	Tan et al. (2015)
	Sales growth	C	QN	Gunasekaran et al. (2018), Akter et al. (2016), Chae (2015) Wamba et al. (2017), Ji-fan Ren et al. 2017, Raguseo and Vitari (2018),
	Satisfaction with inventory control	Q	QL	Chae, Olson, and Sheu (2014a), Chae et al. (2014b), Stefanovic (2015)
	Satisfaction with shop floor control	Q	QL	Chae, Olson, and Sheu (2014a), Chae et al. (2014b),
	Satisfaction with the cost planning	Q	QL	Chae, Olson, and Sheu (2014a), Chae et al. (2014b)
	SC visibility	Q	QN	Zhu et al. (2018), Yadegaridehkordi et al. (2018), Srinivasan and Swink (2018)
	Support to community	Q	QL	Gunasekaran et al. (2018)
	Technology innovation	I	QN	Fernando, Chidambaram, and Wahyuni-TD (2018)
	Transaction costs	C	QN	Hofmann (2017)
	Unit product cost	C	QN	Srinivasan and Swink (2018)
Source	Flexibility to change supplier lead time	T	QN	Fernando, Chidambaram, and Wahyuni-TD (2018)
	Flexibility to change as per supplier needs	F	QL	Fernando, Chidambaram, and Wahyuni-TD (2018)
	Innovative supplier selection process	I	QL	Fernando, Chidambaram, and Wahyuni-TD (2018)
	Procurement flexibility	F	QL	Bock and Isik (2015), Huang and Handfield (2015), Srinivasan and Swink (2018)
	Predictability of procurement fraud	Q	QN	Matthias et al. (2017)
	Relationship with suppliers	Q	QL	Huang and Handfield (2015)
	Responsiveness to supplier needs	T	QL	Fernando, Chidambaram, and Wahyuni-TD (2018)
	Responsiveness to supplier queries	T	QN	Fernando, Chidambaram, and Wahyuni-TD (2018)

(*Continued*).

Table 6. Continued.

BDDSC Process	Performance Measures	Cost (C) Time (T) Quality (Q) Flexibility (F) Innovativeness (I)	Qualitative (QL) Quantitative (QN)	Key References
	Supplier trust	Q	QL	Fernando, Chidambaram, and Wahyuni-TD (2018)
	Supply visibility	Q	QL	Srinivasan and Swink (2018)
Make	Manufacturing cost	C	QN	Brinch (2018), Kwon, Lee, and Shin (2014)
	Capacity flexibility	F	QN	Ali, Ghoniem, and Franke (2014), Stefanovic (2015)
	Detection of machine bottlenecks	Q	QN	Yu and Matta (2016)
	Equipment health	Q	QL	Kumar, Shankar, and Thakur (2017)
	High-performance products	Q	QN	Chavez et al. (2017)
	Low quality losses	Q	QN	Juuso and Lahdelma (2013)
	Maintenance costs	C	QN	Kumar, Shankar, and Thakur (2017)
	Maintenance team availability	F	QL	Arya et al. (2017)
	Make rapid product mix changes	F	QN	Chavez et al. (2017)
	Manufacturing flexibility	F	QN	Chae et al. (2014b)
	Manufacturing quality	Q	QN	Kumar et al. (2016)
	Prediction of product quality	Q	QN	Kim et al. (2018)
	Predictive fault finding	Q	QN	Juuso and Lahdelma (2013)
	Predictive machine failure	Q	QN	Ghattas, Soffer, and Peleg (2014), Juuso and Lahdelma (2013)
	Produce customised products	F	QN	Chavez et al. (2017), Lee (2017), Matthias et al. (2017)
	Product features flexibility	F	QN	Chavez et al. (2017), Srinivasan and Swink (2018)
	Product lifecycle costs	C	QN	Kumar et al. (2016)
	Product Quality	Q	QN	Anwar, Khan, and Shah (2018), Chavez et al. (2017)
	Production efficiency	C	QN	Kumar et al. (2016)
	Production makespan	T	QN	Ali, Ghoniem, and Franke (2014)
	Production visibility	Q	QL	Brinch (2018)
	Rapid change in production volume	F	QN	Chavez et al. (2017)
	Reduced cycle inventory stock	Q	QN	Wong, Potter, and Naim (2011)
	Reduced inventory	C	QN	Kwon, Lee, and Shin (2014), Wong, Potter, and Naim (2011)
	Reduced manufacturing cycle time	T	QN	Kwon, Lee, and Shin (2014)
	Reduced material processing cost	C	QN	Kwon, Lee, and Shin (2014)
	Reduced obsolete inventory stock	Q	QN	Wong, Potter, and Naim (2011)
	Reduced safety inventory stock	Q	QN	Wong, Potter, and Naim (2011)
	Scalability of the production	F	QN	Stefanovic (2015)
Deliver	Reduced distribution costs	C	QN	Kwon, Lee, and Shin (2014)
	Delivery lead time	T	QN	Chavez et al. (2017)
	Delivery performance	Q	QN	Arya et al. (2017)
	Delivery reliability	Q	QN	Chavez et al. (2017), Chae, Olson, and Sheu (2014a), Chae et al. (2014b)
	Improved warehouse operations	Q	QN	Pang and Chan (2017)
	Late deliveries	Q	QN	Jain et al. (2014)
	Responsiveness to customer complaints	Q	QN	Fernando, Chidambaram, and Wahyuni-TD (2018)
	Responsiveness to urgent deliveries	F	QN	Brinch (2018)

(*Continued*).

Table 6. Continued.

BDDSC Process	Performance Measures	Cost (C) Time (T) Quality (Q) Flexibility (F) Innovativeness (I)	Qualitative (QL) Quantitative (QN)	Key References
	Service delivery	Q	QL	Fernando, Chidambaram, and Wahyuni-TD (2018)
	Total delivered cost	C	QN	Srinivasan and Swink (2018)
Returns	Customer feedback	Q	QL	Fernando, Chidambaram, and Wahyuni-TD (2018)
	Customer complaints	Q	QN	Fernando, Chidambaram, and Wahyuni-TD (2018)
	Customer Loyalty	Q	QL	Anwar, Khan, and Shah (2018), Gunasekaran et al. (2018)
	Customer response time	T	QN	Tan et al. (2015), Fernando, Chidambaram, and Wahyuni-TD (2018)
	Customer Retention	C	QN	Akter et al. (2016), Wamba et al. (2017), Ji-fan Ren et al. (2017), Raguseo and Vitari (2018),
	Customer ratings	Q	QL	Wamba et al. (2016)
	Customer reviews	Q	QN	Wamba et al. (2016)
	Customer satisfaction on the order return	Q	QL	Wamba et al. (2016)
	Customer satisfaction	Q	QL	Anwar, Khan, and Shah (2018), Song et al. (2018)
	Customer service level	Q	QN	Lee (2017), Fernando, Chidambaram, and Wahyuni-TD (2018)
	Customer service quality	Q	QL	Anwar, Khan, and Shah (2018)
	Customer trust	Q	QL	Fernando, Chidambaram, and Wahyuni-TD (2018)
	Customers opinions of the products	Q	QL	Wamba et al. (2016)
	Flexibility to change as per customers needs	F	QL	Fernando, Chidambaram, and Wahyuni-TD (2018), Song et al. (2018)
	Market visibility			Srinivasan and Swink (2018)
	Quick refund	Q	QN	Wamba et al. (2016)
	Predicting customer reactions	Q	QL	Wamba et al. (2016)
	Volume of customer reviews	Q	QN	Wamba et al. (2016)

Table 7. Summary of performance measures used in BDDSC measures.

BDDSC Process	No. of measures	Cost/Non-cost measures	Qualitative or Quantitative
Plan	58 (44%)	C: 26 (46%), F: 5 (09%), I: 4 (07%), Q: 16 (28%), T: 05 (09%)	QL: 11 (19%), QN: 47 (81%)
Source	10 (07%)	Q: 03 (33%), T: 3 (33%), F: 2 (22%), I: 1 (11%),	QL: 06 (67%), QN: 03 (33%)
Make	31 (23%)	C: 07 (22%), F: 08 (26%), Q: 14 (45%), T: 2 (07%)	QL: 04 (13%), QN: 27 (87%)
Deliver	15 (11%)	C: 01 (09%), F: 1 (09%), Q: 08 (73%), T: 1 (09%)	QL: 01 (07%), QN: 10 (93%)
Return	17 (13%)	C: 01 (06%), F: 01 (06%), Q: 14 (82%), T: 01 (06%)	QL: 10 (59%), QN: 07 (41%)

Abbreviations: C-Cost, F- Flexibility, I- Innovativeness, Q-Quality, T-Time, QL-Qualitative, QN-Quantitative.

required to set the performance targets for the BDA requirements, so that the relevant information required to evaluate the BDDSC performance is available with the managers without any disruption.

5.2. BDA platform

Information processing needs drive the information processing capability of an organisation. The information processing capability is represented by the second component, 'BDA platform' in Figure 1. A strong BDA capability helps the organisation to achieve improved SC visibility which is defined as 'the extent to which actors within the SC have access to the timely and accurate information that they consider to be key or useful to their operations' (Barratt and Barratt 2011; Barratt and Oke 2007). The BDA platform should provide the organisational support to collect, store, analyse, and share the data as planned in the performance planning stage. The BDA platform consists of tangible and intangible resources such as data collection devices, storage database, internet connectivity, and data analysts. The BDA performance of the organisation should be evaluated against the relevant performance measures listed in Table 5.

5.3. BDDSC performance monitoring

Performance-monitoring stage access the information generated by the BDA platform and performs a real-time performance monitoring of the BDDSC processes on the selected measures. Any deviations in BDDSC performance should be highlighted in the performance monitoring stage so that the organisations can take proactive actions to overcome the performance problems. In contrast to having regular performance meetings in traditional SC to monitor the performance, in BDDSC, we propose to have a highly specialised team of performance managers who will be monitoring and measuring the performance in real-time, sharing the shortcomings with the functional line managers for proactive decision making. The performance managers should possess business, technical and relational domain knowledge and have good coordination with the managers and SC partners responsible for the performance of BDDSC processes. These teams should continuously monitor and review the progress of the selected performance measures and take necessary actions in real-time. The main advantage of BDDSC-PMS over traditional SC PMS is the availability of information on all the measures in real-time. This advantage will help the organisations to overcome the problems of delays in conducting performance reviews due to lack of knowledge or inadequate analytical skills. The main obstacles if any, during the monitoring and review of BDDSC could be the poor BDA capability. However, appropriate measures for evaluating the BDA capability would ensure a robust BDA platform. In the next section, we illustrate the use of BDDSC-PMS.

5.4. Illustration on implementing the BDDSC PMS

5.4.1. Strategic objective

To broaden the existing product offerings.

5.4.2. Sample BDDSC performance measures

The organisation may select the sample performance measures such as; Product Innovation, New product development, New product development success rate, Manufacturing flexibility, Customer feedback, Customer reviews, Customer opinions, Customer Reactions.

5.4.3. Performance targets

The managers would be required to set the performance targets for the above performance measures. These may include the number of product innovations to be done in a year, the number of new products launches to be done in a year, the number of successful product launches, the level of manufacturing flexibility required regarding no. of products to be manufactured at a given facility. It will also include the targets for the number of customer feedback to be obtained at each stage of product development, the number of positive reviews on product usage, type of opinions expected and so on.

5.4.4. Sample BDA capability performance measures

The above-planned performance measures for the BDDSC processes are from the SCOR domain of plan, make and return. These measures will drive the BDA capability, and hence, the performance managers are required to strengthen their BDA capability to connect with the SC partners from these domains. The sample BDA performance measures may include; BDA investments, information access to the product designers, analytical skill sets required by the data analysts, and security level for the consumer data.

5.4.5. Performance targets for BDA capability

Next, the managers will be required to set the targets for the selected BDA capability measures such as level of BDA investments for a specific domain to provide the relevant data, the level of accessibility to be provided, and level of security required.

5.4.6. *Performance monitoring*

The significant outcome of a BDDSC-PMS monitoring process is real-time updates and revisions in the performance measures and the targets. The performance review teams may perform any of the following actions based on the review outcomes. The real-time updates from the customers in the form of reviews, opinions, feedbacks, and reactions will help the designers to be more efficient and expedite the new product development process resulting in successful innovations and product launches thus, improving the SC performance. The BDA capability will help them to predict the success of the product in the future. If at any point it is felt by the organisations that they will not be successful with the product launch they can terminate the project and save losses to the organisation. The performance managers may come across the following situations;

(i) ***No change in the performance measures and targets***: This is the ideal situation for the performance managers where the selected measures and targets contribute to achieving the strategic objectives without any deviations.
(ii) ***Removing the non-contributing or insignificant measures***: Performance managers during the review process may identify that some measures are not contributing as expected towards the strategic objectives or the strategic alternatives may change because of competitive pressures influencing the team to take this decision.
(iii) ***Revision in existing measures through replacing them with more appropriate measures***: This action is an outcome of improved BDDSC processes and BDA capability of the organisation offering them a new set of performance measures that were not available to the team before.
(iv) ***Revising the performance targets:*** The performance team may like to review the targets considering the market dynamism. As the BDDSC-PMS is capable of predicting the future performance, some of the variables (measures) may be expected to contribute highly during the performance monitoring process, and hence the performance team may like to increase the weight assigned to such variables and revise the performance targets.

It is believed that the framework will support the organisations to predict performance problems and be prepared with proactive solutions to overcome them. In the next section, we present the implications and future research directions from the study.

6. Implications and future research directions

The review focused on understanding how the BDA is conceptualised in the SC performance studies, what are the various performance measures used for evaluating the BDDSC performance and how to measure the BDDSC performance. Having reviewed the literature, we find that BDA plays a significant role in influencing the SC performance. The findings reveal that both the performance of BDDSC process and BDA platform are critical in deciding the BDDSC performance, compelling the organisations to develop PMS integrating them. This section presents the managerial implications and the agenda for future research in the field of BDDSC performance measurement.

- The literature highlights that BDA is regarded as an information and knowledge resource that should be exploited for analysing the BDDSC. Therefore, the performance managers should focus on understanding the complexity of the data, monitor, and control the data quality for effective decision-making. The SC managers should take an integrative view of the available analytical or data management tools and techniques instead of focusing on the stand-alone tools. It is required that the future studies should consider promoting a collaborative interdisciplinary approach by involving experts from different domain who would help on maximum utilisation of this resource to have maximum impact on the BDDSC performance.
- Even though the BDA has a positive impact on the BDDSC performance, the success of the organisation depends on the level of BDA capability they possess. The role of top management is found to be highly significant in developing BDA capability (Popovič et al. 2018). The other factors that moderates the influence of BDA on the SC performance includes the strategic alignment between BDA and business (Akter et al. 2016), the adoption stage of BDA (Huang, Wang, and Huang 2018), supplier base complexity level (Jeble et al. 2018), and supply uncertainty (Zhu et al. 2018). SC practitioners should focus on addressing these issues while developing their BDA capability. This will ensure tight alignment between analytics efficiency and strategy. Therefore, the practitioners should ensure that their BDA capability aligns with their strategy. The future research should focus on identifying more number of moderating variables that may affect the relationship between the BDA and the SCP.
- It is found that majority of the performance measures for evaluating the level of BDA capability are quality measures. BDA investment was the only cost measure used by the organisations. The primary motivation for the organisations in making investments in developing BDA is the improvements in their decision-making performance. Compared to other IT assets, BDA is considered as a productive investment, promising lucrative returns.

It is therefore implied that the SC practitioner should quantify the magnitude of the potential SC improvements before deciding to make BDA investments (Müller, Fay, and vom Brocke 2018). The BDA and BDDSC process measures presented in this paper will guide the practitioner's to select the appropriate measures to decide on the expected level of BDA and BDDSC performance. Future research studies should focus on identifying industry-specific performance measures that will further assist the SC practitioners in determining the level of investments they should make on developing their BDA capabilities.

- The impact of BDA is not equal in all the BDDSC processes and varies according to the process maturity level of the SC. For example, de Oliveira, McCormack, and Trkman (2012) reports that the BDA has a low impact on the planning, manufacturing, and delivery process, whereas very high impact on the sourcing, in the level IV and V of SC process maturity level. It is therefore crucial that the SC practitioners should assess their present SC process maturity before making their BDA investments. The process maturity levels impact the information processing needs and thus affects the relationship between BDA and performance results. Future research should focus on identifying the inter-relationships between the BDDSC processes when BDA is deployed within the organisations. For, e.g. the studies should focus on studying the impact on SC visibility and transparency in the source, make, deliver, and return processes when high investments in BDA are made to improve the visibility and performance of planning process.
- It is found that majority of the BDA performance measures represented quality dimensions. Very few measures represented time and flexibility dimensions. While implementing the measures, the practitioners should consider each of the SC processes (planning, source, make delivery and return) separately and evaluate the impact it has on the SC performance. For example, while evaluating the performance of BDA on accessibility, the firm should assess to what extent the BDA system is available over time for making decisions related to planning, sourcing, make, deliver, and return domains. Similarly, the measure 'system integration' refers to the ability to integrate various sources of data coming from different SC process domains to produce meaningful insights. More studies are required to be undertaken to investigate the impact of different BDDSC processes on building the BDA capability.
- Response time is the only time measure used to evaluate the BDA performance. This measure evaluates how fast the BDA system responds to the requests of the various users in the organisation. The practitioners should use this measure for assessing the promptness of the BDA platform. However, more such measures will be required in the future for evaluating BDA performance. For example, how much time is taken for developing and implementing a BDA platform for PMS can act as an important performance measure to assess the speed of implementation. Future research studies may focus on identifying more performance measures, as presently we find the existing measures inclined more on measuring the quality.
- Data-driven culture is an outcome of the organisation culture built over a period and differs across companies. The performance of the BDA on this measure will help the organisations to realise the full potential of big data (Jeble et al. 2018). The practitioners should arrange for a regular meeting and develop transparent communication systems to interact with their SC partners, to sensitise the importance of BDA for the improved SC performance. This will help to overcome any barriers that may arise due to behavioural and political factors. Future studies should focus on identifying strategies that may be implemented to develop a sound data-driven culture in the organisations.
- It is found that none of the measures focused on the evaluation of the BDA on innovativeness dimension. This may be because enhancing the innovation, and product design capabilities of the firm are seen as an outcome of BDA implementation (Chen, Preston, and Swink 2015; Ramanathan et al. 2017; Wamba et al. 2015). Therefore, the performance measures representing the innovativeness dimensions are included in the BDDSC process and not under BDA measures. The practitioners should consider the above point while evaluating the performance of BDDSC on innovativeness measures.
- The performance measures for BDDSC processes as presented in Table 6 apply to both manufacturing and service industries. However, the importance attached to these performance measures may vary across companies. For example, an online company (e-tailer) may assign more weight for return domain (customer satisfaction) while a manufacturing firm may not consider this measure for evaluation. The practitioners are required to select the relevant measures carefully. Future studies will be needed to identify more industry-specific performance measures so that the practitioners can use them as ready reckoners.
- There is an emergence of new measures as an outcome of the big data predictive analytics capability. The predictive analytics capability will allow the firms to go beyond understanding what has happened in the past by providing the best estimations of what may occur in the future. The predictive analytics capability has given rise to many new measures, which we have identified in our study to evaluate the BDDSC processes. Few of the measures

include predicting accurate forecasts, machine failure rates, detecting frauds, and predicting vehicle arrival rates. The practitioners should include these measures for improving the performance of BDDSC. Future research studies should focus on developing new predictive analytics based applications for logistics and SCM. With the increasing development in the field of machine learning techniques and artificial intelligence, it is expected that big data predictive analytics will be providing more business value to the organisations. The focus of the researchers should be on developing such performance measures.

- Our study also identifies new performance measures in the return domain. The previous studies on traditional SC have identified customer satisfaction or dissatisfaction as a significant performance measure. However, with the rise of social media which is a substantial source of big data, a new set of measures based on social media analytics are presented in our study. These measures will provide valuable insights to the SC practitioners and help them to improve their marketing performance by incorporating the real-time customer insights into their strategies. However, more research studies are required to be conducted in the future on investigating how the insights received from social media analytics can be used by the organisations to improve the firm's performance. Presently, very few studies deal with examining the relationship between the BDA and its influence on SC performance for an electronic commerce company. Some performance measures are required to be developed in this sector.
- The practitioners after identifying the relevant performance measures should classify or rank the measures based on the degree of its importance. They should continuously monitor the changes in the environment and update the significance assigned to these performance measures. The performance measures are found to evolve based on changing business environments. For example, our study explores new performance measures in the return domain, which otherwise were few before the advent of BDA. More studies are required to examine such measures from time to time. The present study also identified a list of measures to evaluate sustainable SC performance. This indicates that the practitioners are acknowledging the role of BDA in achieving sustainable SC performance. The practitioners can track their green gas emissions, contribution towards the poverty reduction or savings on fuel consumptions to evaluate their sustainable SC performance.
- More studies will be required to be conducted in future on BDDSC with the focus of identifying innovativeness, flexibility and time measures, as presently they lack in number, compared to the cost and quality measures.

7. Conclusions, limitations, and scope for future studies

A BDDSC is different from the traditional SC as it is concerned to find what events are occurring in the real-time and what will happen in the future. A BDDSC has a futuristic view and can offer meaningful insights on measuring the predictive performance of the organisations. The review suggests that the BDA is conceptualised as an organisational resource which is required to be used effectively and economically. It is therefore essential to evaluate how the organisations perform on the BDA capability.

Furthermore, the review indicates that the performance measures used for BDDSC processes are different from the traditional SC measures. The BDDSC measures are required to be monitored and tracked in real-time, demanding actions from the performance managers without much delay. The findings of the study reveal that to achieve predictive BDDSC performance; the organisations should have an integrated performance measurement system that combines both the performance measures of BDA and BDDSC processes. Our study identified and collated 130 measures for BDDSC processes and 25 measures for BDA capability. The BDA and BDDSC performance measures were classified on the dimensions of cost/non-cost measures and quantitative/qualitative measures. Additionally, the SCOR domains were used for organising the performance measures for BDDSC processes. The proposed BDDSC-PMS framework will help the practitioners in implementing the PMS in their BDDSC.

The research papers for the review were extracted from the Scopus database. The selection of the keywords was made considering the scope of the study. However, it is possible that it might not have included some significant papers relevant to the scope of the study. Studies in the future may review the search and selection criteria used in this study and validate the findings. Further, the BDA and BDDSC performance measures identified in this study need to be validated by the industry practitioners. In the future, industry-specific case studies on determining the industry-specific performance measures may be conducted. In this study, we have used pre-determined classification schemes available from the literature to categorise the defined performance measures. The future studies may survey industry practitioners and use factor analysis for validating the categories used in this study. Studies are also required to be conducted to validate the BDDSC-PMS framework proposed in this study. The outcomes of such studies may be incorporated in revising the framework and making it more robust.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Appendix A: Journal wise distribution of papers

Journal Name	No. of Publications
International Journal of Production Research	8
Decision Support Systems	6
International Journal of Production Economics	5
International Journal of Operations & Production Management	3
Production Planning & Control	3
Benchmarking: An International Journal	2
Information Systems Frontiers	2
Information and Management	2
International Journal of Information Management	2
International Journal of Logistics Management	2
International Journal of Physical Distribution & Logistics Management	2
Journal of Business Research	2
Journal of Management Information Systems	2
International Journal of Productivity and Performance Management	2
Business Process Management Journal	2
International Journal of IS Modeling and Design	1
Journal of Business Intelligence and Data Mining	1
Journal of Organization and End User Computing	1
Business Horizons	1
International Journal of Logistics Research and Applications	1
International Journal of Computer Integrated Manufacturing	1
International Journal of Information Systems	1
International Journal of Information Technology & Decision Making	1
Journal of Business Logistics	1
Journal of Computational Science	1
Journal of Enterprise Information Management	1
Journal of Information System and SCM	1
Journal of Information and Knowledge Management	1
Journal of Intelligent Manufacturing	1
Journal of Operation Research Society	1
Journal of Organizational and End User Computing	1
Journal of Quality in Maintenance Engineering	1
Production and Operations Management	1
Strategic Decisions	1
Technological Forecasting and Social Change	1
Information System Research	1
Total	66