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Unfolding the link between big data analytics and supply chain planning

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ABSTRACT

Big data analytics (BDA) has captured growing research interests in operations and supply chain management literature, yet, despite the significant implication, extant knowledge falls short in drawing the link between BDA and supply chain planning (SCP) with in a structured manner. This paper employs the Delphi technique to uncover the synergies between BDA technology, conceptualized as big data sources and BDA methods, and the SCP activities framed with the SCP matrix. The panel runs for three rounds with 35 experts including scholars, supply chain practitioners, and BDA specialists. The results of this paper suggest that the relevance of BDA depends on the focal SCP activity. Thirty-five projections are presented on the expected impact of BDA on SCP that are classified into three groups based on the significance of impact and probability of occurrence. This work advances the understanding of BDA in supply chain management drawing implications to prioritize BDA investment for SCP.

1. Introduction

Relying on the use of data emerging from within and across the organizational boundaries, supply chain planning (SCP) refers to the set of processes and activities related to the development of plans to guide the operation of supply chains by translating requirements into feasible programs while optimizing outcomes under given constraints (APICS, 2017; Supply Chain Council, 2012). Owing to the exponential growth of available and accessible data, SCP activities ranging from demand forecasting, production planning to inventory sizing and allocation are significantly affected by the advancement of digital technologies and analytics (Waller and Fawcett, 2013).

Big data analytics (BDA) is the application of advanced analytics to big data – considered as datasets exhibiting properties of high volume, variety, velocity, value, and veracity showing elevated frequency in data generation and significant heterogeneity in the source and format of data (Fosso Wamba et al., 2015; Tiwari et al., 2018) – to extract meaningful patterns and insights from the vast amount of data to inform decision-making (Arunachalam et al., 2018; Wang et al., 2016; Xu et al., 2021). Provided notable implications to the way companies collect, analyze and process data, the rise of BDA demonstrates significant potential in enhancing business operations and forecasting, which resulted in the growth in recent research attention at the intersection between BDA and SCP (Andersson and Jonsson, 2018; Schlegel et al., 2020; Xu et al., 2021).

While the benefit of BDA in operations and supply chains has been widely discussed, it is lacking a systematic understanding of how BDA can be linked to SCP. This can help in evaluating investments of BDA adoption and implementation, that require significant financial efforts and the development of BDA-related competences (Brinch et al., 2018; Hofmann and Rutschmann, 2018; Lai et al., 2018). To date, existing literature on linking BDA to SCP either takes a broad perspective discussing the implication of BDA on a selection of SCP issues (e.g. (Tiwari et al., 2018; Wang et al., 2016)), or focuses on developing conceptual and analytical models and algorithms for specific SCP tasks (e.g., (Zhong et al., 2015a)). These perspectives, however, are not adequate to guide decisions on prioritizing BDA investment for specific SCP process need. Thus, this paper aims to address the following research questions in bridging the promises of BDA technology and its actual impact on SCP:

RQ1: How is BDA technology aligned with the SCP process need?

RQ2: How will BDA technology impact the future of SCP?

The objective of this study is threefold. First, the paper is set to understand the alignment between BDA technology and SCP need, considering BDA technology as a set of sources and analytic methods and SCP as a set of activities characterized by distinctive needs and specificities. Second, it attempts to clarify the impact of BDA on SCP based on the perception of experts. Third, this paper aims to inform organizational BDA adoption actions and elucidate prominent directions for

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future investigation of BDA for SCP. This study answers to the call of empirical research to advance the knowledge of BDA use in supply chains (Kache and Seuring, 2017) enriching the literature of supply chain analytics (Souza, 2014; Wang et al., 2016), and argues that BDA is time- and scope -dependent with respect to the context (Brinch et al., 2018; Hofmann and Rutschmann, 2018).

The paper is structured as follows: Section 2 introduces the research background by presenting the relevant literature. Section 3 explains the research design and choice of research methodology. The main findings of the study are presented in Section 4 and discussed in Section 5. The paper concludes with the contribution to literature and management and an overlook to the limitations.

2. Research background

2.1. Big data and big data analytics

As compared to traditional datasets, big data offers higher versatility and advantages to the realm of operations and supply chain management since the field commonly employs analytical methods and algorithms to optimize decisions (Choi et al., 2018). According to its feature, big data can be broadly classified into structured, semi-structured, and unstructured data (Rozados and Tjahjono, 2014). Typical *structured* data are standardized numbers and strings stored within organizational databases, such as transaction records, that can be relatively easy to analyze without extensive effort in data preparation (Minelli et al., 2013). *Unstructured* data, instead, may take diverse formats, ranging from text, audio, video, geospatial information, emails, and internet log, which consequently implies extensive effort in data treatment before being able to fed into analytic models to extract insight (Dubey et al., 2018; Minelli et al., 2013). Supply chain related-big data sources are many, that goes far beyond the traditional structured sources (Minelli et al., 2013), such as the core transactional data. Organizations, nowadays, may elaborate on data from internal systems concerning production and operations, as well as other external data sources which are more complex and requires further investment, e.g. smart objects, clickstream data, and social media data collected from the online platforms (KPMG, 2017; Rozados and Tjahjono, 2014; Xu et al., 2021).

BDA models refer to a wide range of analytical methods and techniques applicable in the big data context (Choi et al., 2018), falling in a taxonomy of descriptive, predictive and prescriptive analytics (Nguyen et al., 2018; Souza, 2014; Tiwari et al., 2018; Wang et al., 2016). *Descriptive analytics* refers to BDA methods aiming at identifying problems by describing the current situation (e.g. description and visualization) to answer question of what is happening. Statistics, characterization, and discrimination are examples of the descriptive methods. *Predictive analytics* aim at projecting and forecasting the future based on the history and present. These include BDA methods like clustering, classification, forecasting, association, regression, and semantic analysis. Lastly, *prescriptive analytics* encompasses algorithms and techniques in determining and assessing alternative solutions. Examples of prescriptive analytics are simulation and optimization. Tiwari presents a shortlist of BDA methods relevant for the supply chain domain, which entails classification, regression, clustering, association, visualization, semantic analysis, graphical analysis, optimization, and simulation (Tiwari et al., 2018).

2.2. Big data analytics and SCP

While supply chain management broadly covers the activities of design, planning, execution, control and monitoring of the flow of goods and information, the planning of supply chains specifically focuses on the asset coordination between supply chain members with a forward-looking perspective, aiming to balance supply and demand and to optimize the delivery of goods, services and information and to balance supply and demand (Jonsson and Holmström, 2016; Stadtler et al., 2015; Xu and Pero, 2023). Evidence from literature supports the value of BDA in the planning of all core supply chain processes (Stadtler et al., 2015), including sales, procurement, production and distribution (Sanders, 2016; Souza, 2014; Talwar et al., 2021; Wang et al., 2016).

Sales and demand planning (SAL) is the planning phase of customer orders considering the historical data, trend and seasonality, life cycle of the product and exceptional influences that are expected to happen. Forecast accuracy lies at the center of demand planning and fulfilment. Extant discussion converges to the statement that, the use of user-generated social network data (Boone et al., 2018; Choi, 2018) and customer reviews (Salehan and Kim, 2016), BDA will significantly improve demand forecast and reduce forecasting errors (Nguyen et al., 2018; Souza, 2014; Talwar et al., 2021; Wang et al., 2016) at both mid-term (Boone et al., 2019; See-Tso and Ngai, 2018) and short-term (Sagaert et al., 2018). The impact of BDA in improving independent forecasting techniques and gaining insights on end-user consumption (Brinch et al., 2018) is also evident to practitioners, leading to the potential towards a completely data-driven demand planning in supply chains (Roßmann et al., 2018).

Procurement planning (PRC) stands for the planning of purchasing and material requirement, covering the decision of procurement quantities taking into consideration the results from the bill of materials explosion, leadtime and capacity constraints. BDA is capable to support the development of effective sourcing strategies (Wang et al., 2016) and optimize supplier selection through multi-criteria decision-making techniques (Lamba and Singh, 2017; Moretto et al., 2017; Nguyen et al., 2018; Wang et al., 2016) using specific cost-modeling or risk-assessment tools to evaluate suppliers. The acquisition of these information increases the firms' bargaining power in negotiations while enhancing collaboration with key suppliers (Brinch et al., 2018; Sanders, 2016).

Production planning (PRD) encompasses master planning, production planning and scheduling, defining the use of available production capacity of one or more facilities dealing with seasonal demand fluctuations while tackling decisions of lot-sizes and sequences on the machines in the short-term. Studies on the use of BDA on production planning are evidently more matured than the other processes, leveraging on the advancement of real-time data stream from IoT and smart objects (Nguyen et al., 2018; Tiwari et al., 2018). Relying on different analytics, big data fuels up the optimization of cycle time prediction (Wang et al., 2018), production scheduling (Wu et al., 2018), shop floor management and material handling (Ji and Wang, 2017; Talwar et al., 2021; Zhong et al., 2017, 2015b), inventory planning for internal production systems (Tiwari et al., 2018), as well as resource allocation based on the production mix (Wang et al., 2016).

Distribution planning (DIS) concerns the planning of material flow within the production network, the transportation of goods to customers, as well as between sites in the distribution channel. The process is overwhelmed with data emerging from internal (e.g., GPS data, shipment information) and external sources (e.g., traffic and weather conditions), leaving an ample field for BDA in improving logistic network design (Ilie-Zudor et al., 2015) and route optimization (Lamba and Singh, 2017; Nguyen et al., 2018; Sanders, 2016; Talwar et al., 2021). Indeed, the use of BDA in distribution planning leads to the reduction of planning lead times, process interruptions, increased traceability, a better estimation of truck arrival time (van der Spoel et al., 2017), and improved fuel efficiency and vehicle maintenance (Lamba and Singh, 2017). Table 1 reports the findings from literature.

Despite the extant knowledge on BDA in SCP, we highlight three major research gaps. Firstly, the literature shows scattered contribution on a selection of planning process (e.g., production, logistics, and product development), centered around the discussion of BDA application for individual SCP activities. It falls short in presenting a structured overview of how the available BDA methods and techniques can be related to the overall SCP process, and weather there are synergies between BDA methods and source of big data (Hofmann and Rutschmann, 2018). A structured overview of how BDA can be linked to the entire

Table 1
Relevant literature on BDA for SCP.

	Planning horizon	SCP issue	BDA model[a]			BDA method	Big data source[b]			Big data source (details)	Reference
			DES	PRE	PRS		S	Sem	U		
Sales	Long-term	Strategic sales planning		x		Regression, clustering, classification		x	x	Macro-economic data; demographic trends; technological trend	(Brinch et al., 2018; Chehbi-Gamoura et al., 2020; Nguyen et al., 2018; Roßmann et al., 2018; Souza, 2014; Talwar et al., 2021; Wang et al., 2016)
	Mid- term to short-term	Mid/Short-term demand forecasting		x		Forecasting, regression, clustering, classification	x	x	x	Customers' purchasing data; behavior and satisfaction; MRP data; social media data; customer review data; Google trend data. Real time information about fluctuations in demand; POS data	(Boone et al., 2019, 2018; Chehbi-Gamoura et al., 2020; Choi, 2018; Nguyen et al., 2018; Ren et al., 2019; Sagaert et al., 2018; See-Tso and Ngai, 2018; Souza, 2014; Talwar et al., 2021; Wang et al., 2016)
		Demand sensing		x		Semantic analysis			x	Online customers' review data; Social network data	(Nguyen et al., 2018; Salehan and Kim, 2016)
Procurement	Long-term	Strategic sourcing and suppliers' selection	x	x	x	Description and visualization, optimization, Regression		x	x	Supply market trends and suppliers' inputs and economics (e.g., cost, quality, delivery speed, delivery reliability, sustainability…)	(Chehbi-Gamoura et al., 2020; Lamba and Singh, 2017; Moretto et al., 2017; Nguyen et al., 2018; Roßmann et al., 2018; Souza, 2014; Wang et al., 2016)
	Mid-term to Short-term	Tactical sourcing (auctions and contracts)		x		Optimization		x	x	Suppliers' inputs and economics (e.g., cost, quality, delivery speed, volume flexibility, sustainability…)	(Brinch et al., 2018; Sanders, 2016; Souza, 2014)
Production	Long-term	Supply chain network design: optimal location and allocation			x	Optimization	x			Yearly aggregate demand per product and retailer; plant capacities; costs (annual shipping costs, fixed costs…); ERP data	(Ilie-Zudor et al., 2015; Souza, 2014; Talwar et al., 2021; Wang et al., 2016)
	Mid-term to Short-term	Manufacturing, scheduling, and control	x		x	Description and visualization, classification, optimization, modeling and simulation		x		More granular data thanks to IoT; sensors and real-time available data	(Chehbi-Gamoura et al., 2020; Koot et al., 2021; Nguyen et al., 2018; Souza, 2014; Talwar et al., 2021; Wang et al., 2016; Wu et al., 2018)
		Inventory planning (in production system)		x		Forecasting		x	x	Data coming from customers; internal production data	(Nguyen et al., 2018; Talwar et al., 2021)
		Cycle time prediction		x		Forecasting, clustering		x		Intelligent equipment and IoT data	(Wang et al., 2018)
		Shop-floor management and material handling			x	Optimization	x	x		RFID data; real-time and multi-source data; monitoring systems data; shop floor capacity data	(Ji and Wang, 2017; Talwar et al., 2021; Zhong et al., 2017, 2015b)
Distribution	Mid- term and short-term	Logistics/ Transportation planning	x	x	x	Description and visualization, optimization, regression, classification		x	x	Shipping costs; delivery and pickup time windows; business and capacities data; RFID tags; GPS data; weather and traffic data	(Chehbi-Gamoura et al., 2020; Koot et al., 2021; Lamba and Singh, 2017; Nguyen et al., 2018; Souza, 2014; Talwar et al., 2021; van der Spoel et al., 2017; Wang et al., 2016)

[a] DES - Descriptive analytics, PRE – Predictive analytics, PRS – Prescriptive analytics.
[b] S – Structured data, Sem – Semi-structured data, U – Unstructured data.

span of SCP is not yet presented. Nonetheless, there is an overwhelmed interest in researching BDA support to operational decision-making (i.e., short-term decisions) as compared to more strategic ones (i.e., mid- and long-term decisions) (Koot et al., 2021). Contribution of BDA to long-term orientation is rarely investigated (Xu et al., 2021). Finally, being an emerging technology that continues to evolve, it is not clear how supply chain scholars and practitioners can prioritize BDA-related effort in supply chain research and practice. We believe that research on BDA in supply chains should be pragmatic and future-oriented (Culot et al., 2020) with the attempt to close the gap between theory and practices.

3. Research design and methodology

In seek of unfolding the link between BDA technology and SCP, this study turns to a future-oriented research method to elucidate and forecast the relevance of BDA method and big data sources on SCP activities drawing on the knowledge from experienced academics and industrial experts. A Delphi study was conducted considering the fragmentation of extant application with the aim to derive implications based on the consensus from knowledgeable individuals (Barrios et al., 2021; Flostrand et al., 2020; Linstone and Turoff, 2002, 2011; von der Gracht, 2012) while assuring anonymity, iteration of results over rounds, controlled feedback and statistical group response (Mitchell, 1991; Rowe and Wright, 1999). Our study follows a standard research design for the Delphi technique, including the definition of the number of Delphi rounds and execution process, decision on experts sampling, and data analysis (Beiderbeck et al., 2021; Krægpøth et al., 2017).

3.1. The Delphi study process

We adopt the Delphi research method with three consecutive rounds in consistence with previous studies in supply chain research (e.g., Brinch et al., 2018; Kache and Seuring, 2017). Based on an inductive and qualitative approach, the first round is set to brainstorm and identify prominent BDA methods and big data sources for each SCP activity and draw projections on the impact of BDA in the next five years. In particular, the SCP activities are conceptualized in twelve clusters according to the core supply chain process (i.e., sales, procurement, production and distribution) the time horizon (i.e., long-term, mid-term, short-term) (Stadtler et al., 2015) (see Fig. 1). The result triangulates and enriches the evidence from literature integrating the answers collected from the panel. The response from these open-ended questions were coded and analyzed in lists of BDA methods and big data sources, and projections were elaborated for the expected impact of BDA on SCP. We document the results in a report together with a supplementary glossary of definitions and examples.

The second-round aims to evaluate the results obtained from the first round. With reference to the report from first-round result and the glossary, the panelists are asked to rate the prominence of BDA methods and big data sources for each SCP activity and prioritize the projections of impact in terms of their *probability of occurrence* and *significance of impact* based on a 5-point Likert scale.

Finally, the third-round aims to provide an opportunity to the panel members in reviewing and adjusting the opinions based on the result distribution of the overall panel, provided a report with statistical analysis of the panel response from the second round (e.g., mean values, standard deviation, and quartiles) and the glossary.

The process of data collection was conducted online based on a predefined protocol (see excerption in Appendix 1). For each round, the report and glossary are sent together with the invitation. The panelists could answer the survey at their convenience within a given time window.

3.2. Selection of the panelists

There is no strict standard in literature on the optimal number of Delphi panel participants. We followed the rule of thumb by assuring the observation of repetitive patterns from the brainstorming session to grant saturation (Giunipero et al., 2012). We compiled an extensive database of potential panelists including: *i)* scholars – key contributors from identified publications on advanced technologies for supply chain management or SCP (Mitchell, 1991), *ii)* practitioners – experienced supply chain practitioners at the management level or beyond from diverse industries, and *iii)* technology specialists – BDA experts or consultants from supply chain solution providers. We managed to reach out to 348 experts from multiple channels (e.g., university connections, professional email, LinkedIn) for the initial invitation, and the final panel is formed up by 35 members who accepted and contributed to the research. The panel composition is reported in Appendix 2.

3.3. Data analysis

The qualitative data analysis in the first-round open-ended questions employs both open- and deductive coding, taking reference to the result that emerged from the a priori literature review. The whole research team has discussed and prepared a shared protocol for the coding process and a codebook for reference. Two researchers coded the responses individually, and the result from the two coders was compared and discussed to ensure every misalignment is resolved before the next round. Then, the codes were standardized, and similar codes were merged into groups for the development of categories (Corbin and Strauss, 1990; Roßmann et al., 2018). To ensure a mutual understanding of the terminologies, the final categories resulted from the coding process, together with their definition, were circulated with the panelists through a glossary document. An example of the coding process is presented in Appendix 3.

In particular, we conceptualized the big data sources with analogy to the supply chain risk literature concerning supply chain risk sources (Jüttner et al., 2003), and the resulted supply chain-relevant big data sources fall into three categories depending on its origin: organizational sources, supply network sources and external environmental sources. Organizational data lies within the boundaries of the supply chain actor emerging from internal operations and productions (e.g. machine-state data), labor and core transactions (e.g. ERP data). Supply network-related data arise from interactions between organizations within the supply network, often concerning the operation and performance of supply network partners (e.g. distribution network data, data on supplier performance). Environmental data refers to data arising from the interaction of the supply network with the external environment, involving the activities and phenomena which are beyond the control of

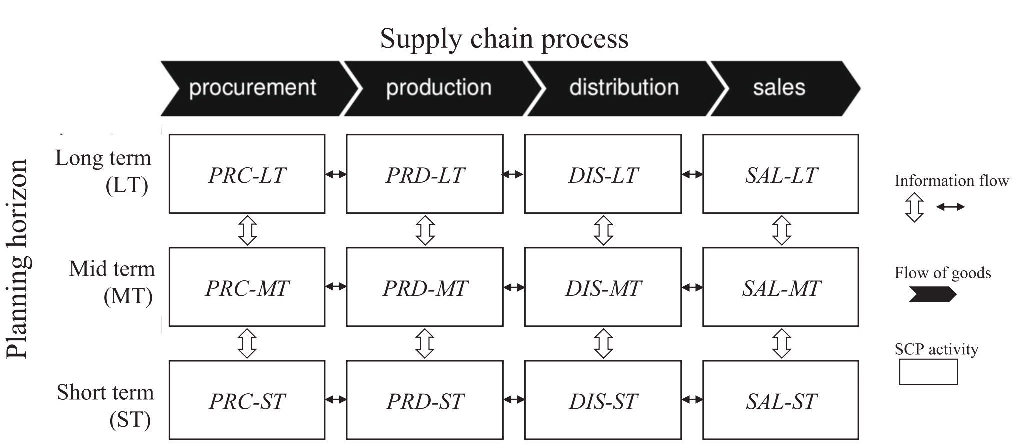

Fig. 1. SCP activities (adapted from Stadtler et al., 2015).
Note to abbreviation:
Sales and demand planning (SAL), procurement planning (PRC), production planning (PRD) and distribution planning (DIS).
Long-term (LT), Mid-term (MT), Short-term (ST).

the supply network, including data on weather or traffic.

Quantitative data are collected from the second and third rounds, which is primarily analyzed with descriptive statistics. A k-mean cluster analysis is performed on the normalized values in the third round result to identify similar representative patterns to derive projections (Peppel et al., 2022; Roßmann et al., 2018). As measure for the research rigor, we check the progress stability with variation of the mean value between two successive rounds (i.e., consistency), and compute the interquartile range (IQR) as the measure of convergence (IQR < 1) among all experts with reference to existing literature (Barrios et al., 2021; von der Gracht, 2012). We relied on the non-parametric Kruskal-Wallis' test (Seuring et al., 1952) to validate if responses from the three independent sub-panels demonstrate any statistical significance (i.e., $p < 0.05$) as the data does not follow the normal distribution. In cases of low convergence, a pair-wise comparison with the Mann–Whitney method (Ilin et al., 1945) is conducted to further explore differences across the three sub-groups of panelists (i.e., scholars, practitioners, experts from solution providers), exploring if significant differences are present (i.e., $p < 0.05$) across the type of respondent.

4. Result

4.1. On the link between BDA and SCP activities

Result on the prominent BDA methods for SCP activities is visualized in Fig. 2 and the quantitative assessment is reported in Table A3 in appendix. The ten methods are noted as descriptive analytics (i.e., description and visualization, characterization and discrimination), predictive analytics (i.e., clustering, forecasting, association, classification, regression, semantic analysis), and prescriptive analytics (i.e., simulation, optimization).

As shown in Fig. 2, the value of these BDA methods is context-dependent, where the relevance is subject to the focal SCP activity defined by the supply chain process and time horizon of the planning (refer to Fig. 1 for acronyms). Overall, while a high relevance of big-data-driven *forecasting* can be observed in all activities, *simulation* plays an essential especially for long- to mid-term planning activities and *optimization* stands out particularly for short-term production and distribution planning. This result also affirms that the integration BDA can further enhanced traditional methods for SCP. On the contrary, the relevance of semantic analysis is questioned by the panel, showing the lowest level of relevance for all SCP activities. Although being a rapidly emerging BDA methods, its contribution to SCP may not be as evident as other business functions.

Regarding big data sources for SCP, the panel converges to a total of 32 distinctive sources ($n_{SAL} = 16$, $n_{PRC} = 16$, $n_{PRD} = 19$, $n_{DIS} = 21$). The result is presented in Fig. 3, with further quantitative Delphi assessment reported in Table A4 in appendix. Comparing to BDA methods, the context-dependency of the relevance is more evident for big data sources, where several data sources serve a selection of SCP activities exclusively. Overall, SAL reports the significant use of big data from organizational and environmental sources, highlighting the relevance of *data on competitors*, *macroeconomic data*, and *organizational strategy and financial data* for the long-term, and *sales and transactions*, and *forecast*, *operating conditions*, and *customer information* for the mid- to short-term. PRC values big data from organizational and supply network sources. In short-term planning, data from *operating conditions*, *ERP systems* and *marketing and promotion* dominate the operational activities, while *macroeconomic data* are of higher relevance for long-term strategic procurement planning. *Supplier performance* as transversally important for all planning horizons. A similar pattern is observed in PRD where organizational and supply network big data are positively evaluated. *Data on operating conditions* outstand all planning horizons, followed by *supply chain visibility data* and *organizational and production system data*. A combined use of *forecast big data* is more likely to dominate long-term PRD, while *production process big data*, *data on replenishment* and *data*

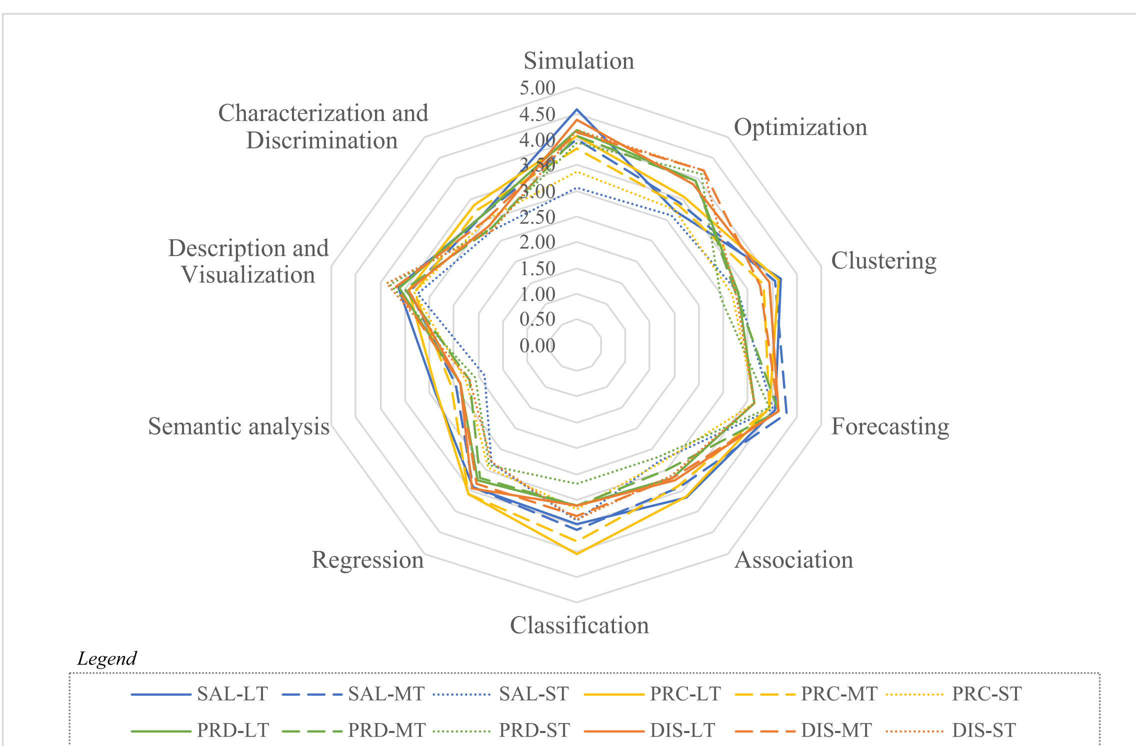

Fig. 2. Delphi result on the relevance of BDA methods for SCP activities
Note to abbreviation:
Sales and demand planning (SAL), procurement planning (PRC), production planning (PRD) and distribution planning (DIS).
Long-term (LT), Mid-term (MT), Short-term (ST).

Fig. 3. Delphi result on the relevance of big data sources for SCP activities
Note to abbreviation:
Sales and demand planning (SAL), procurement planning (PRC), production planning (PRD) and distribution planning (DIS).
Long-term (LT), Mid-term (MT), Short-term (ST).

on machines and smart objects shows increased relevance in the short-term. Finally, DIS benefits from a wider range of sources, showing the potential to integrate more traditional datasets (e.g., *forecast data*, *customer demand and requirement*), data from the distribution network (e.g., *data on warehouses and inventory*), and other emerging data sources for the SCP activities (e.g., *weather data* and *traffic data*).

4.2. Scenarios of BDA for SCP in the next five years

To assess the future scenarios of BDA for SCP, the Delphi results are synthesized to 35 projections on the impact of BDA on SCP activities triangulating the responses from the open-ended questions from the first round and the extant literature (Table 2). The research team carefully reviewed the generated projections to assure clarity, reasonableness, and plausibility and emotional neutrality (Peppel et al., 2022; Rowe and Wright, 1999), and analyzed the quantitative data to produce the scenario analysis.

For SAL, the use of BDA is expected to result in significant improvement in forecasting accuracy and flexibility, thus, leading to better customer service level, reduction of stock and costs, and avoidance of stockout. BDA-driven market analysis supports product programs definition in the long-term, while revolutionizing mid-term planning by introducing higher visibility on customers and market. Eventually, short-term activities benefit from the use of a wider set of data sources and automatic forecast adaption. The predominant contribution of BDA for PRC lies in the empowerment of fast response to procurement disruptions by risk detection and improved performance on accuracy and better material programming. BDA empowers the process of collaborative planning with suppliers and supplier negotiation in achieving more favorable contract terms, and it also enables the integration of sustainability considerations. Concerning PRD, the impact of BDA is acknowledged in facilitating mid- to short-term optimization in master production scheduling, capacity plans, inventory plans and shop floor planning. Better planning performance is also the result from the improved supply network design and production system design. Similarly, BDA support DIS in distribution network design and warehouse replenishment with real-time and granular consumption data. BDA improves the overall DIS performance enabling the integration of risk management and sustainability-oriented goals while empowering distribution make-or-buy choice and investment, distribution planning and personnel scheduling.

Table 2 also reports the quantitative assessment on significance of impact and probability of occurrence referring to a 5-point Likert scale, where it shows that the average of significance of impact for the projections ranges from 3.75 (PRD03) to 4.50 (DIS10), while the average of probability of occurrence ranges from 2.94 (PRD03) to 4.00 (PRD09). This result may be explained by the potential gap between the enthusiasm in the theoretical discussion in literature and the unclarified BDA application and adoption in reality. In general, the higher value of probability of occurrence in short-term SCP activities indicates a higher level of maturity in extant development as compared to long-term decisions.

The projections are separated into three clusters based on the k-mean cluster analysis on normalized values following the rule of nearest mean (Fig. 4). Besides the explicit differences on significance of impact and probability of occurrence, the three clusters also demonstrate peculiarities in other patterns. Projections that directly address improvement of performance in the planning activities are captured by *cluster 1*, showcasing how advanced analytics can be directly integrated into the extant planning process drawing on big data sources of higher granularity. The SCP activities addressed in this cluster are mainly well-structured planning tasks with an elevated level of standardization, which provide the ground for optimization model development to assist planning – e.g. master production scheduling and capacity planning (PRD08) and distribution and warehouse systems (DIS07). Adjustments and rescheduling of production are made possible thanks to the high speed and granularity of big data. Meanwhile, projections with a more explorative nature which relies on the integration of a wider range of data sources to excavate the value of big data is captured by *cluster 2*. With the empowerment to the extant planning process to achieve higher flexibility and capabilities as the common theme, the impact to the planning performance occurs in an indirect manner. For instance, BDA supports supplier negotiation relying on unstructured data on suppliers, thus, improving contract terms (PRC09), and it facilitates demand

Table 2
Projections of BDA impact on SCP activities with quantitative Delphi result.

Code	Horizon	Projection	Significance of impact			Probability of occurrence			Cluster
			Mean	SD	Std. Val[a]	Mean	SD	Std. Val	
SAL01	Overall	Improve forecasting accuracy in Sales and demand planning, which leads to better customer service level, reduction of stock and costs, and avoidance of stockout.	4.47	0.5	2.08	3.76	1.1	1.11	1
SAL02	Overall	Improve flexibility and automation in Sales and demand planning	3.94	0.9	−0.69	3.82	0.8	1.33	2
SAL03	Long-term	Support product programs definition by empowering market analysis to detect new business opportunities	3.88	0.7	−1.00	3.06	1.1	−1.52	3
SAL04	Mid-term	Revolutionize mid-term sales planning for the visibility it brings on customers and market	4.24	0.7	0.85	3.35	1.0	−0.43	1
SAL05	Short-term	Empower short-term sales planning and demand planning for individuals with customer-generated big data	3.88	1.0	−1.00	3.76	0.8	1.11	2
SAL06	Short-term	Facilitate automatic forecast adaption (update) according to customer behavior in real-time	3.94	0.9	−0.69	3.41	1.0	−0.21	2
Process average of Sales and demand planning (SAL)			*4.06*		*−0.07*	*3.53*		*0.23*	
PRC01	Overall	Improve Procurement planning performance (e.g. higher planning accuracy, cost reduction, better material program, order management)	4.13	0.6	0.27	3.31	0.7	−0.58	3
PRC02	Overall	Empower fast response to procurement disruptions by prior risk detection	4.25	0.6	0.93	3.56	0.7	0.35	1
PRC03	Overall	Integrate sustainability into Procurement planning (e.g. greenhouse gas reduction, waste management)	4.06	0.9	−0.05	3.50	1.0	0.12	2
PRC04	Overall	Improve the quality of supplies as the outcome of Procurement planning	3.94	0.7	−0.71	3.19	0.9	−1.04	3
PRC05	Long-term	Enable the detection of procurement-related trends in long-term Procurement planning	4.06	0.9	−0.05	3.31	0.8	−0.58	3
PRC06	Long-term	Facilitate collaboration with suppliers in long-term Procurement planning	4.19	0.8	0.60	3.00	1.2	−1.74	3
PRC07	Long-term	Empower supplier selection and supply base definition by using more granular supplier performance data (e.g. price, quality, delivery performance) in long-term Procurement planning	4.00	0.7	−0.38	3.56	0.9	0.35	2
PRC08	Mid-term	Support optimization in inbound inventories of raw materials and components (e.g. stock reduction, stockout reduction)	3.94	0.9	−0.71	3.81	1.0	1.29	2
PRC09	Mid-term	Empower supplier negotiations and improve contract terms by scenario analysis with more accurate big data	4.13	0.8	0.27	3.56	0.9	0.35	2
PRC10	Short-term	Improve process standardization and automation in materials ordering in short-term Procurement planning	3.75	0.9	−1.69	3.44	1.0	−0.11	3
Process average of Procurement planning (PRC)			*4.04*		*−0.15*	*3.42*		*0.16*	
PRD01	Overall	Improve Production planning performance (e.g. higher planning accuracy, better customers service level, cost reduction)	4.00	0.8	−0.38	3.69	0.8	0.82	2
PRD02	Overall	Empower fast response to production disruptions through prior risk detection	4.06	0.9	−0.05	3.50	0.8	0.12	2
PRD03	Overall	Integrate sustainability into Production planning (e.g. emission and waste reduction)	3.75	0.9	−1.69	2.94	0.9	−1.98	3
PRD04	Long-term	Enable the detection of production-related trends and growth opportunities in long- term Production planning	3.94	0.9	−0.71	3.25	0.9	−0.81	3
PRD05	Long-term	Empower supply network design (e.g. production plant location, warehouse location) with the use of better and new data sources	3.81	0.9	−1.36	3.31	0.8	−0.58	3
PRD06	Long-term	Empower production system design (e.g. production capacity sizing, plan layout, asset and equipment investment) by scenario analysis and simulation	4.00	0.8	−0.38	3.38	1.2	−0.35	3
PRD07	Mid-term	Support optimization of production inventories (e.g. stock reduction, stockout reduction)	4.25	0.8	0.93	3.75	1.1	1.05	1
PRD08	Mid-term	Support to optimizations in master production scheduling and capacity planning	4.38	0.6	1.58	3.63	1.1	0.59	1
PRD09	Short-term	Support machine scheduling and optimization of lot-sizing at shopfloor level with timely capacity adjustments and re-scheduling based on machine-state and operational data	4.13	0.7	0.27	4.00	1.0	1.99	2
Process average of Production planning (PRD)			*4.04*		*−0.20*	*3.49*		*0.10*	
DIS01	Overall	Improve Distribution planning performance (e.g. better customer service level, cost reduction, higher planning accuracy)	4.25	0.6	0.93	3.50	0.7	0.12	1
DIS02	Overall	Empower fast response to distribution disruptions through prior risk detection	4.25	0.6	0.93	3.50	1.0	0.12	1
DIS03	Overall	Integrate sustainability into Distribution planning (e.g. reduction of carbon footprint)	4.13	0.7	0.27	3.06	0.9	−1.51	3
DIS04	Long-term	Enable the detection of long-term distribution-related trends	3.81	0.9	−1.36	3.19	1.0	−1.04	3
DIS05	Long-term	Empower distribution network design concerning location of distribution centers, warehouses and deposits	4.31	0.6	1.26	3.75	0.9	1.05	1
DIS06	Long-term	Empower distribution make-or-buy choice and investment justification in long-term Distribution planning (e.g. workflow aggregation, better distribution mode selection)	4.06	0.6	−0.05	3.13	0.9	−1.28	3
DIS07	Mid-term	Support inventory optimization in distribution systems and optimization of warehouse layout	4.19	0.7	0.60	3.69	0.9	0.82	1
DIS08	Mid-term	Empower mid-term distribution planning and personnel scheduling (e.g. workflow aggregation, better distribution mode selection) with more granular and new data sources	3.88	0.9	−1.03	3.25	1.3	−0.81	3
DIS09	Short-term	Support to short-term transportation planning with use of real-time data to reduce waste and time	4.06	0.7	−0.05	3.69	1.1	0.82	2
DIS10	Short-term	Improve planning of warehouse replenishments with real-time and granular consumption data	4.50	0.6	2.24	3.75	1.2	1.05	1
Process average of Distribution planning (DIS)			*4.14*		*0.37*	*3.45*		*−0.07*	

[a] Std.Val = Standardized value.

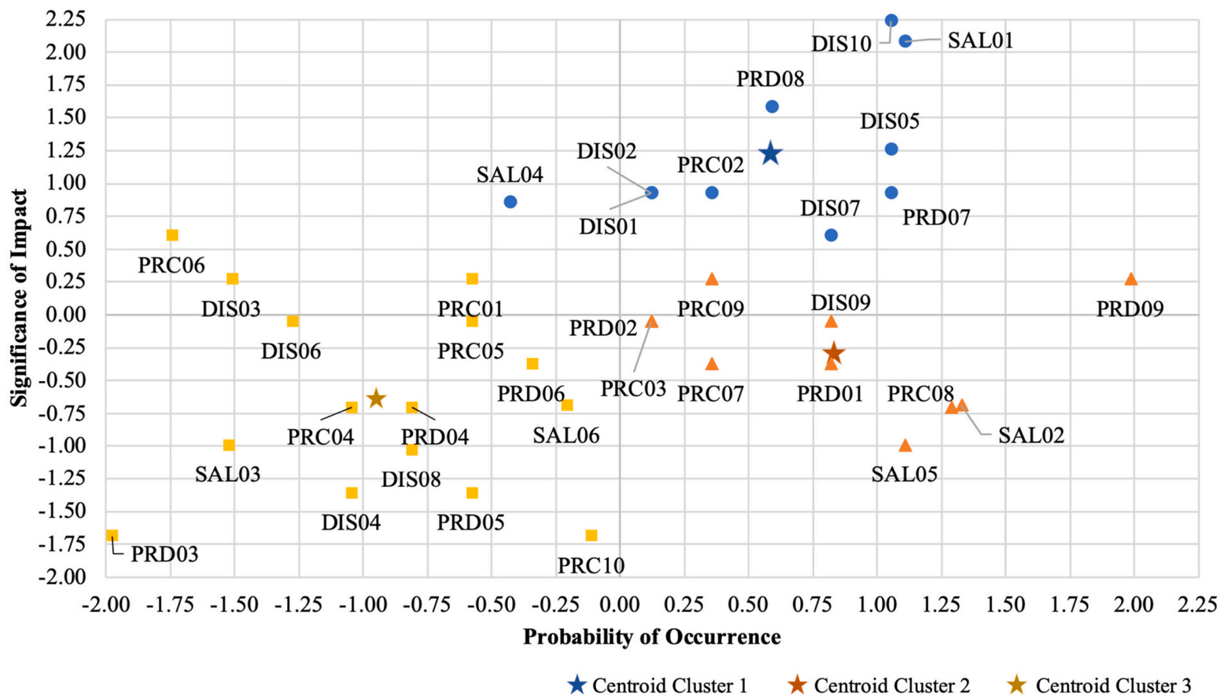

Fig. 4. Cluster analysis on BDA projections
Note to abbreviation:
Sales and demand planning (SAL), procurement planning (PRC), production planning (PRD) and distribution planning (DIS).

individualization with customer-generated big data, thus, improving sales planning accuracy (SAL05). Finally, *cluster 3* are characterized by projections with evolutional change to SCP activities, associated to the introduction of strategic changes in the planning objective. These projections address long-term considerations, such as facilitating sustainability integration (e.g., DIS03), enabling detection of trends and growth opportunities (e.g., PRD04), and empowering strategic make-or-buy decisions (DIS06) and production system design (PRD06). The result is more likely to be a decision support dashboard rather than a direct output (e.g., a number in forecast) which requires consequent human intervention in the decision-making process, and additional enablers such as supply chain integration. Thus, the lower level of probability of occurrence, as compared to the other two clusters, can be explained by the significant challenges when facing these projections considering the current phase of BDA development.

4.3. Perceptual differences within the panel

Table 3 reports the seven cases of statistical difference across the type of respondents (i.e., scholars, supply chain practioners, and BDA specialists) from a total of 417 assessments (1.6 %). No other differences are identified, which reinforces the validity of the Delphi study showing the convergence of experts' perceptions on BDA for SCP.

Overall, the major differences fall in the perception of big data sources, where *data on policy and regulation* is identified with the highest divergence among all subpanels in long-term planning decisions. The result indicates different ratings between scholar, practitioner, and technology expert in 3 out of the 4 supply chain processes (i.e., PRC, PRD and DIS). In general, scholars hold higher expectations as compared to practitioners and solutions providers. Such differences in perception may be the result of how their daily activity is affected by regulations,

Table 3
Sub-panel difference (*p*-value ≤0.05).

ID	Question	Questionnaire section	Kruskal-Wallis test (p-value)	Mann–Whitney test (p-value)[a]		
				Scholar vs. practitioner	Scholar vs. technology specialist	Practitioner vs. technology specialist
1	To what extend do you think [*data on policy and regulation*] is relevant to [*long-term*] [*distribution planning*]?	Big data source – SCP activity	0.016	0.048	0.020	0.027
2	To what extend do you think [*data on policy and regulation*] is relevant to [*long-term*] [production planning]?	Big data source – SCP activity	0.033	/	0.020	/
3	To what extend do you think [*data on policy and regulation*] is relevant to [*long-term*] [*procurement planning*]?	Big data source – SCP activity	0.048	0.028	/	/
4	To what extend do you think [*forecast data*] is relevant to [*short-term*] [*production planning*]?	Big data source – SCP activity	0.036	0.040	/	/
5	To what extend do you think [*big data forecasting*] is relevant to [*short-term*] [*sales and demand planning*]?	BDA method – SCP activity	0.029	/	/	0.034
6	To what extend do you think [*big data feature selection*] is relevant to [*short-term*] [*sales and demand planning*]?	BDA method – SCP activity	0.043	/	/	0.049
7	To what extent do you think [*Improve flexibility and automation in Sales and demand planning*] is probable to occur in the next 5 years? (i.e. SAL2)	Projection	0.014	0.040	0.037	0.027

[a] Note: cells with "/" indicate p-value > 0.05.

thus contributing to a different sense of relevance.

Divergence is also observed concerning BDA for short-term SAL. While practitioner and technology expert showed different perceptions on the relevance of big data forecasting and feature selection, the perceptual difference is observed among all the three subpanels for the probability of occurrence that BDA affects flexibility and automation in short-term SAL. Among all, technology experts hold the highest expectation, followed by the practitioners and scholars. Such effect may be attributed to the difference in technological knowledge and the knowledge on the BDA solutions developed in the current stage.

5. Discussion

5.1. Unfolding the link between BDA and SCP

"Processing data with the wrong method results in false impressions" (Hofmann and Rutschmann, 2018). Drawing on the previous result, several propositions can be derived to advance the existing knowledge on the link between BDA and SCP activities (Table 4).

BDA brings considerable influence on sales and demand planning activities due to the drastic increase of both the depth and width of datasets. Organizational and environmental data are highly valued in the era of big data, where predictive and prescriptive BDA methods can be applied on customer-centric and customer-generated big data to derive more accurate forecasts. In the long-term, product, placement, pricing and promotion related big data are at the center of demand forecasting activities (Hofmann and Rutschmann, 2018), while exogenous macroeconomic variables can drive changes in sales as leading indicators in demand forecasting (Sagaert et al., 2018). For short-term planning, BDA helps to excavate relationships between online-product sales and product ranking, as well as customer-generated big data such as customer reviews and reviewers' profile (Hou et al., 2017). Therefore, while the integration of a wider variety of real-time datasets presents an evident challenge to demand planning, the performance improvement in planning is promising in terms of accuracy, flexibility, level of automation and visibility (Roßmann et al., 2018).

Procurement planning embrace several opportunities for process improvement in the area of supplier selection, supply base definition and supplier negotiation, with the major performance improvement in increased accuracy, cost reduction, better material programming and order management. Organizational data concerning internal production, demand and spent (Moretto et al., 2017; Wang et al., 2016), together with supply network data such as supplier performance, evaluation and risk of disruption, contributes to sourcing strategy decisions once combined with BDA-driven simulation (Ivanov, 2017). Supply network data also supports the identification, assessment and mitigation of supply risks with predictive and prescriptive models (Ivanov, 2017; Roßmann et al., 2018; Tiwari et al., 2018). Environment data concerning the macroeconomy and regulations, or even public news and social media, enhances procurement decision efficiency (Tiwari et al., 2018; Wang et al., 2016). Thus, all three streams of big data sources are relevant for the planning of supply, while data accessibility remains a challenge to reveal the potential of BDA since it may require strategic collaboration between supply chain partners as a prerequisite. As procurement planning lies at the boundary of the organizations, data management and sharing, besides the technical advancement of analytics, should receive higher attention.

BDA introduces performance improvement in production planning in terms of planning accuracy, better customers service level, cost reduction, and process automation. Organization big data is at the center of production planning, primarily concerns the internal operations of an organization, where data on capacity, availability, constraints, and forecast are fed to the simulation and optimization-based BDA methods (Culot et al., 2020). The advancement of digitalization and connectivity has presented a wide variety of data sources from the Internet of Things (Feng and Shanthikumar, 2018; Roßmann et al., 2018), enabling data

Table 4
Propositions on the link between BDA and SCP.

ID	Supply chain process	Planning horizon	Proposition
Proposition 1a	Sales and demand planning	Long-term	BDA-driven simulation, clustering and forecasting improves forecasting accuracy and visibility on customers and market in sales forecasting based on organizational and environmental big data.
Proposition 1b	Sales and demand planning	Mid- to short-term	BDA-driven forecasting improves automated update in sales forecasting based on customer-generated organizational and environmental big data.
Proposition 2a	Procurement planning	Long-term	BDA-driven clustering, classification, simulation, and forecasting improves supplier selection process, supply base definition and supply quality in procurement planning based on all streams of big data sources.
Proposition 2b	Procurement planning	Mid- to short-term	BDA-driven forecasting improves inbound inventories optimization and supplier negotiation in procurement planning based on organizational and network data.
Proposition 3a	Production planning	Long-term	BDA-driven simulation and optimization supports supply network design, production system design and capacity planning, improving the overall performance in production planning (mainly) based on organizational data.
Proposition 3b	Production planning	Mid- to short-term	BDA-driven forecasting, simulation and optimization supports master production scheduling, production inventories, machine scheduling and lot-sizing (mainly) based on organizational data.
Proposition 4a	Distribution planning	Long-term	BDA-driven simulation, forecasting, clustering, and optimization supports distribution network design, improving the overall performance in distribution planning (mainly) based on organizational and supply network data
Proposition 4b	Distribution planning	Mid- to short-term	BDA-driven optimization, simulation, forecasting, and data description and visualization supports personnel scheduling, transportation planning, inventory optimization and warehouse replenishments in distribution planning based on all streams of big data sources.
Proposition 5	Transversal	/	BDA-driven simulation, clustering, forecasting, and optimization enables the integration of strategic considerations in SCP related to sustainability, trend detection, and fast response to disruptions based on all streams of big data sources.

processing for diagnostics and production control with machine learning and artificial intelligence in the cyber-physical systems (Zhang et al., 2020; Zhong et al., 2015a). Supply network data, more precisely supply chain visibility data, also has a minor contribution in production planning in informing the materials availability in the production stage.

As for distribution planning, planning accuracy, customer service level, cost reduction, and process automation can be improved with the integration of BDA into the planning system. In the long-term, the primary contribution can be attributed to the supply network data, concerning supply chain risks and distribution network data, and organizational data, concerning aggregated demand and warehouses and inventory (Wang et al., 2016). Shared personal information of the customers assist to personalize delivery network management (Peppel et al., 2022). Short-term transportation planning receives additional support from environmental data, where real-time information on traffic and whether appear as the game-changer in the big data era. BDA model with data description and visualization could assist real-time allocation of fleet and stocks, thus, supporting optimizations in the network flow problems and crew routing (van der Spoel et al., 2017; Wang et al., 2016). The enhanced transparency provided by BDA also contribute to the management of returns flows, and eliminates drivers that trigger returns (Roßmann et al., 2018).

There are several impacts of BDA transversal to the overall entire planning process, especially considering strategic changes, showing the potential to revolutionize SCP. however, realization of these initiatives is beyond the development of a simple conceptual model. Besides improvement in efficiency and effectiveness, the panel affirms that BDA can support organizations in introducing new objectives to the planning process, shifting from the traditional goal of SCP (Xu et al., 2021). Strategic decisions are highly influential to all the consequent planning stages; thus, they frequently involve collaboration between human and machines to arrive at the final choice. It is expected that SCP will undergo transformations when BDA technology intercepts human intervention to support SCP decisions, where advanced analytics can be used to interpret human language and behavior. At the same time, the effectiveness of BDA systems depends on how they are perceived and used. To date, there is fragmented understanding on the interaction and collaboration between supply chain planners and BDA technology, concerning the integration of human knowledge and BDA results, as well as trust issues of BDA methods (Li et al., 2008, 2004). There is no BDA methods nor standardized solutions ready for immediate use (Kache and Seuring, 2017; Sodero et al., 2019), thus, technological capabilities is also relevant to be addressed by future research.

5.2. Managerial implications from the future projections

Fig. 5 presents all projections of BDA impact on SCP in a two-by-two matrix according to the significance of impact and probability of occurrence. Reading this result with respect to the three projection clusters and assuming higher probability of occurrence would be associated to lower effort in implementation, we provide the following implications to support decisions on SCP-related BDA action prioritization. These implications suggest organizations can firstly focus on the areas where BDA investment would expect high return on SCP performance, and consequently extend the technology investments to leverage synergies and develop a complete portfolio.

With high significance of impact and high probability of occurrence, cluster 1 is considered as "*quick-wins*" since it offers immediate improvement on planning performance (e.g., forecast accuracy, inventory allocation, production scheduling and capacity planning, and distribution planning), attacking the automation and standardization of process and the integration of internal supply chain processes within an organization (Wang et al., 2016). Organizations can achieve quick result through actions of *quick-wins*, since the high probability of occurrence can be attributed to the relatively matured research status of BDA applied in these activities. The focus is, therefore, to enhance the

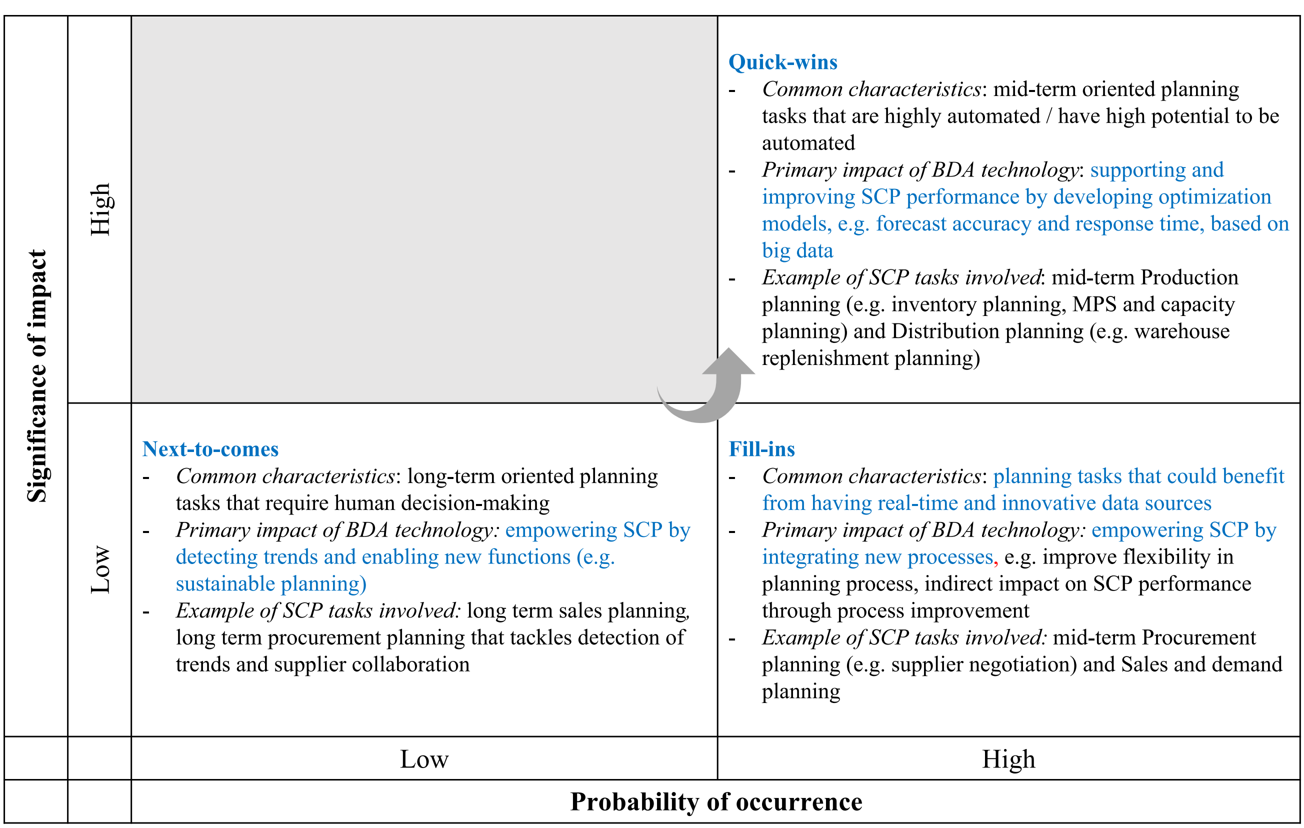

Fig. 5. Action priority matrix of BDA for SCP projections.

effectiveness of supply chain processes through the integration of additional data sources.

With moderate significance of impact but high probability of occurrence, cluster 2 projections are "*fill-ins*" as they target the improvement of supply chain flexibility in reaction to changes which relies on the integration of new data sources (e.g., customer-generated big data) to empower new SCP activities. The focus on short and mid-term planning activities (e.g., short-term sales and demand planning, short-term transportation planning) is facilitated by the quasi-real time monitoring of supply chain and activities, as well as the high rate of automation and standardization of processes based on big data (Wang et al., 2016). Despite the extant research on the potential applications in this category is relatively at an early stage (e.g. (Boone et al., 2019; Choi, 2018)), the high probability of occurrence attributes to the clear view on the potential new data sources to be integrated into SCP.

With moderate significance of impact and probability of occurrence, projections in cluster 3 suggest that BDA will support human decision making by detecting trends, while enabling a more in-depth analysis of the implications of planning on sustainability performance. The SCP activities in this cluster are typically require human intervention and the alignment between the implementation of the BDA application and the business context as strategic goals and organizational culture (Wang et al., 2016). Despite the lower probability of occurrence, it still provides interesting insights on the potential of BDA on planning activities while still a lack of clear insight from research and practice on how BDA contributes to these SCP activities. Organizations need to develop and acquire capabilities to enable BDA adoption. Big data is considered as a complementation than a substitution of human intelligence. Supply chain data science requires both quantitative skills and domain knowledge, and the integration of human factors and the cognition of ideas and concepts from human language and visual communication (Handfield et al., 2019) remain key challenges for future development (Waller and Fawcett, 2013).

5.3. Research implications

Big data exhibits novel properties of increased granularity and close-to-real-time data collection and processing compared to traditional SCP datasets, thus, advanced analytics based on big data significantly improves the accuracy and flexibility of the planning activities (Wu et al., 2018; Zhong et al., 2017). Results from our study generally aligns to extant literature, while several similarities and discrepancies are observed indicating potential directions for future research.

Firstly, *prescriptive BDA* methods (e.g., simulation and optimization) are highly relevant for SCP, especially for production and distribution. This echoes the finding from the literature analysis, where investigations on prescriptive models for production are well populated. As for distribution planning, the panel provided a relatively lower rating for *predictive* BDA models as compared to extant literature, while there are existing discussion on the use of BDA to support collaborative logistics network development (Ilie-Zudor et al., 2015), improve on-time estimation in short-term fleet scheduling (van der Spoel et al., 2017), transforming the "forecasting" into "nowcasting" (See-Tso and Ngai, 2018). The panel also seems to be more conservative when coming to issues of strategic sourcing and supplier assessment, since the actual problem can be too complex to be modelled, where the suggestion is to lean towards explorative methods based on descriptive and predictive analytics. As a result of the extended depth (i.e., number of records) and width (i.e., variety of input labels for each record), the complexity of model development drastically increases due to the increasing number of variables introduced by big data. Yet, prescriptive models are still highly acknowledged for the value it brings to SCP by integrating emerging data sources such as customer reviews and social media information to enrich the planning insight from traditional datasets (Ren et al., 2019). To this end, there is an ample space for further development of activity-specific BDA methods, especially for PRC and DIS which are less addressed by extant literature, and for planning activities with long-term focus.

The study shows that supply network data is gaining momentum in big data-driven planning. The statement particularly holds true for the SCP activities at the intersection between organizations (e.g., PRC, DIS), highlighting the importance of supply chain collaboration and relationship management as prerequisites for inter-organizational data sharing strategy and practices. Meanwhile, organizational data still shows a significant contribution to SCP, indicating that firms should not overlook the value of organizational data in big data-driven SCP since data stored in the internal systems are strategic digital assets (Sodero et al., 2019). Environmental big data, such as customer reviews data, Google trend data on sales forecasting (Boone et al., 2018; Choi, 2018; See-Tso and Ngai, 2018), traffic and weather data (van der Spoel et al., 2017), receives growing research attention. On the one hand, as organizations nowadays are collecting and storing more data than what they can manage, research may further explore how organizational big data, extended in the dimensions of volume, variety, and velocity, will contribute to SCP before diving into integrating external data sources. On the other hand, the variety of big data can be referred to as the integration of emerging data sources. While literature unveiled some insight on applying BDA with environmental data, research on this type of data source is still at an infant stage that has not moved far beyond conceptual model development and pilot case validation. Investigation to explore the use of these new sources remains a promising research stream, where further development should address the challenges brought by the use of environmental data, which are generally characterized by low-value density and require extensive effort to excavate insight (Rozados and Tjahjono, 2014).

Moreover, while extant literature seldom addresses the use of BDA in supporting planning long-term activities, the panel reaches consensus that some BDA methods are particularly relevant for strategic decisions. For instance, the difference in relevance of *simulation* between SAL-LT (4.59) and SAL-ST (3.06) is as significant as 1.53. The perspectives from the experts affirm that BDA methods, especially prescriptive analytics, are highly relevant to long-term planning activities, however, extant research effort deviates from this perception with relatively less attention addressed to long-term planning activities Long-term SCP activities show higher reliance on aggregated level big data (e.g., *macro-economic data,* and *supply chain risk*) to guide consequent supply chain execution and operations, while short-term planning is more likely to embrace novel unstructured big data sources (e.g., *weather data* and *traffic data*), echoing the increasing uncertainty emerging from the external environment that affects the planning and operation of supply chains. The research gap on how BDA and big data at the aggregate level support long-term planning is evident. Further investigation is needed to examine whether and how big data could be used to generate impact on long-term planning activities, while its contribution to short-term planning activities is already evident as a result of higher velocity, granularity, and variety of data sources. For future studies, we encourage future development to further explore the identified links between BDA methods and SCP, further elucidating how the various SCP activities would benefit from the 5Vs (*volume*, *variety*, *velocity, veracity, and value*) of big data (e.g. (Hofmann, 2017)). Studies on BDA methods for SCP should also address the compatibility with existing planning models and clarify the potential of integration to extant SCP process (Xu and Pero, 2023).

Nonetheless, the scenarios derived from the projections present insight for future research, where the three clusters represent the priority for the future to come. Provided the high significance of impact and probability of occurrence, BDA for performance improvement will generate the most significant implication (*quick-wins*), while the understanding of BDA targeting ambitious change to SCP activities (*next-to-comes*) should be further clarified. As BDA is still a technology under evolution, future research should see the position of the projections in the matrix is also dynamic in nature subject to technological advancement.

6. Conclusion

While BDA is receiving growing research interests in the supply chain domain, literature lacks a systematic understanding on how BDA can be linked to SCP. Meanwhile, such understanding is important to support decision-making concerning the prioritization of SCP-related BDA investment and indicate areas that worth future investigation. As such, with reference to the near future, this paper is set to explore how BDA technology is aligned with the SCP process needs and how BDA technology will impact SCP.

The paper is developed drawing on the result of a Delphi study, analyzing the consensus obtained from experts from scholars, practitioners, and BDA technology experts. The results report the relevance of BDA methods and big data sources against SCP activities and indicates how BDA technology can support various SCP activities in the near future. To this aim, this paper presents, in the form of propositions, which big data source and BDA method should be used for each SCP activity. Moreover, it provides indications on which SCP activity will benefit the most in the near future.

In particular, the panel reached consensus that BDA can have positive impacts on planning accuracy, response time and SCP flexibility. The strong impact of BDA on SCP depends on its ability to support the introduction of data-driven optimization models and new data sources to feed SCP models, while assuring process automation. In the short term, BDA is more likely to impact short and mid-term SCP processes. Depending on the nature of the process, BDA can support optimization and automation, as in the case of production and distribution planning, while it can support process improvement actions in the case of procurement, and sales and demand planning. It is less probable that the applications of BDA will interest long-term planning activities. However, interestingly, if properly developed and used, according to the experts' opinions, BDA can contribute to build sustainable and resilient supply chains.

This research contributes to both research and practice. We highlight areas of interest for proposing applications of BDA to a specific SCP, while contributing to the debate on how BDA can support supply chain sustainability and resilience. Future research can take reference to the propositions in this paper, especially the ones as *quick-wins*, to extend existing knowledge and develop further method and models. The results can also be of interest to practitioners. Firstly, this paper inspires the understand which BDA method and source is more promising in each SCP process. Second, with the action priority matrix, this paper presents a guide to support decisions on SCP-related BDA investment, indicating which SCP activities will be more likely affected while offering significant positive results.

We acknowledge several limitations in this paper. First, despite our effort to guarantee rigor along the research process (e.g. panel selection, shared glossary), the results may subject to the experts' knowledge and perception of big data and BDA methods. Second, BDA is an emerging technology under constant advancement. Therefore, our results should be interpreted as a snapshot of how the current (and near future) BDA capabilities match the need of SCP activities where a low chance of occurrence may evolve and may indicate a higher significance of impact to SCP. If radical advancement is observed in the future, a repetition to this study would be applaudable with a broader panel of experts from different disciplines. Additionally, future studies may narrow down to a sub-theme arose in this study concentrating the exploitation of specific big data sources or on the development of conceptual and analytical models for specific SCP problems. Research should not overlook the importance to address how organizations can integrate BDA into their business processes in supporting SCP, and how hurdles of BDA application can be eliminated to fully reap the benefits of BDA application in SCP.

CRediT authorship contribution statement

Jinou Xu: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Project administration. **Margherita Pero:** Investigation, Writing – review & editing, Supervision. **Margherita Fabbri:** Methodology, Formal analysis, Writing – original draft.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.techfore.2023.122805.

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