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Increasing the effectiveness of procurement decisions: The value of big data in the procurement process

Antonella Moretto[a,*], Stefano Ronchi[a] and Andrea S. Patrucco[b]
[a]*School of Management, Politecnico di Milano, Piazza Leonardo da Vinci 32, Milan, Italy*
[b]*Penn State University, Monaca, PA, USA*

Abstract. Big data are a commonly discussed topic, and their value in marketing and sales has been thoroughly investigated. Although some authors have also discussed their relevance to purchasing and supply management, the literature on this topic remains scant. This paper aims to investigate the role of big data in supporting the procurement process and the implementation of procurement practices. The main benefits of such procurement practices for companies are highlighted.

By presenting the results of a focus group of procurement professionals and experts and discussing four exploratory case studies (supported by secondary data analysis), the paper addresses 1) how (and in which format) big data affects different activities in the procurement process and 2) which benefits procurement professionals can expect from adopting big data.

Keywords: Purchasing and supply management, procurement process, big data analytics

1. Introduction

Big data is one of the most commonly discussed topics today, and the most companies are attentively monitoring the evolution of this trend. Several studies have shown that managers are able to make the best decisions when armed with data and tools to gather insight (Davenport, 2006). However, data analysis has become more challenging; nowadays, around 80% of data is unstructured or semi-structured and almost impossible to analyze using traditional methods (Syed, Gillela, & Venugopal, 2013). The relevance of this phenomenon has been quantified; Perrey, Spillecke, and Umblijs (2013) report that a 15–20% increase in ROI can be achieved by introducing big data to enterprises' business analytics.

Gartner's (2012) glossary defines big data as "high-volume, high-velocity and high-variety information assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision making." Several other authors have defined big data in terms of the 3Vs (e.g., Laney, 2001; Hu, Wen, Chua, & Li, 2014): Volume (the large amount of data considered), Velocity (the frequency or speed of data generation), and Variety (the huge variety of data sources and formats).

Many departments within companies are supported by big data, such as marketing, sales, finance, and product development (e.g., Erevelles, Fukawa, & Swayne, 2016; Xu,

*Corresponding author: Antonella Moretto, School of Management, Politecnico di Milano, Piazza Leonardo da Vinci, 32 20133 Milan, Italy. E-mail: antonella.moretto@polimi.it.

Frankwick, & Ramirez, 2015). Similarly, effective supply chain management is increasingly relying upon data to gain insight into expenditures, identify trends in costs and performance, and support process control, inventory monitoring, production optimization, and process improvement efforts (Waller & Fawcett, 2013). Thus, big data seems to be an emerging technology that could dramatically transform the management of inbound supply chain activities and improve companies' competitiveness (Hazen, Boone, Ezell, & Jones-Farmer, 2015). Traditionally, purchasing and supply management (PSM) has strongly relied on data management, as procurement managers need to dispose of, clean, and update data of different natures in order to compare suppliers' performance and improve their savings (and other performances). However, in spite of the relevance of data management, the PSM field has been relatively slow to identify the potential role of new technologies in research and practice (Chae & Olson, 2013; Hazen et al., 2015). Although some pioneering studies have focused on new technologies' importance (Chae, 2015), their practical impact has not been thoroughly analyzed.

In line with these considerations, this paper aims to shed more light on the contribution of big data to the procurement process and its potential impact on companies' performance. In order to explore this issue, we first ran a focus group to obtain procurement managers' perceptions of the phenomenon and identify which phases of the procurement process can benefit more from big data support. Then, due to the exploratory nature of this study, we conducted four case studies in multinational companies to understand the practical contribution of big data to each phase of the procurement process as well as its impact on companies' performance. The paper is organized as follows. In the next section, the main findings of previous research regarding big data analytics and big data's impact on the procurement process are reported. Then, the research framework and research questions are presented. Finally, the main results and conclusions are presented and discussed, and the main contributions of the paper are clarified.

2. Theoretical background

Today, companies are nearly overwhelmed with massive amounts of data concerning customers, suppliers, and potential markets due to new digital technologies. This information is a source of power (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011) that remains useless if it is not properly exploited. A recent Accenture study on senior executives found that, while 97 percent of the sample understood how big data could benefit their supply chain management, only 17 percent implemented it in practice (Accenture, 2014). In order to more fully understand the literature, we must first identify what big data and analytics are and then identify opportunities to revolutionize supply chain management through their use.

2.1. Big data and big data analytics

Big data usage and diffusion in business management is a new area of research that can be investigated from different points of view. There are three main streams of research, discussed below.

The first stream of research aims to provide a proper definition of "big data," as opposed to "big data analytics." Most of the definitions proposed in the literature are based upon Laney's (2001) 3Vs model, but some works try to integrate this perspective with other attributes to extend the meaning of "big data" (e.g., Gandomi & Haider, 2015; Gartner, 2012; Russom, 2011; Wamba, Akter, Edwards, Geoffrey, & Gnanzou, 2015; White, 2012).

The traditional Volume-Velocity-Variety framework can be combined with the following attributes:

- Value, for the economic benefits of big data and the importance of data processing outcomes; big data should be employed not only for the sake of analytics but also to create value for the firm (Tan, Zhan, Ji, Ye, & Chang, 2015).
- Veracity, for the importance of data quality; collected data are often unreliable and hiding some source of uncertainty. In fact, according to IBM (2012), 80% of all data is uncertain.
- Variability, for the ability to recognize the meaning of data in the context in which they are placed. While variety usually refers to the heterogeneity of data, in this case, variability refers to the different meanings that the same data can assume in different contexts (Hopkins, 2011).

This perspective on big data analytics is primarily operational, as it usually refers to analytical tools and applications that aim to extract and manage large amounts of company data. The International Data Corporation (IDC) defines big data platforms as "a new generation of technologies and architectures designed to extract value economically from very large volumes of a wide variety of data by enabling high-velocity capture, discovery, and/or analysis" (IDC, 2015). This definition refers to 1) Laney's (2001) 3Vs model, 2) an emphasis on value creation, and 3) the importance of adequate technological support. A more comprehensive definition of big data analytics is proposed by Krishnan (2013), who states that "Big Data analytics can be defined as the combination of traditional analytics and data mining techniques along with large volumes of data to create a foundational platform to analyse, model, and predict the behaviour of customers, markets, products, services, and the competition, thereby enabling an outcomes-based strategy precisely tailored to meet the needs of the enterprise for that market and customer segment."

The second stream of research on big data has focused on creating a comprehensive classification of the available sources of data on which companies can rely. Hu et al. (2014) present a classification based on analytics domains with five categories: structured data, text data, web data, network data, and mobile data. Rozados and Tjahjono (2014) propose a three-fold classification based on the volume (and velocity), variety, and nature (core, internal, or other) of data. They also extended this taxonomy to include the destination of data within a company. Connaughton and Sawchuk (2014) identify seven categories of data sources: sensor data, social data, transactional data, operational data, partner data, machine-to-machine data, and cloud-service data. Focusing our attention on supply chain data sources, we can identify, among others, EDI data (invoices, purchase orders), procure to pay (p2p) records, supplier ratings (internal and external), delivery times, raw material price indices and volatilities, supplier relationship management (SRM) transaction data, supplier capacity, suppliers' customers, supplier financial performance information, competitor pricing, and supplier location data (Rozados & Tjahjono, 2014).

Finally, the third stream of research addresses big data adoption. Some authors describe the impact of these instruments on the broader field of supply chain management (e.g., Schlafke, Silli, & Moller, 2013). Specifically, Hazen et al. (2015) address data quality management, Chae (2015) studies the implementation of analytical instruments for social network data, and Dutta and Bose (2015) outline the characteristics of a big data project roadmap.

2.2. *Big data analytics to support supply chain management*

Operations performance can be significantly improved by the process of mining (Diamantini, Genga, Potena, & van der Aalst, 2016). Supply chain management is a field in which big data and big data analytics have obvious applications. Until recently, however, businesses have been less quick to implement big data analytics in supply chain management than in other areas, such as marketing or manufacturing (Waller & Fawcett, 2013).

Big data represents a new era of supply chain management, as it is a critical source of meaningful information that can help supply chain stakeholders to gain improved insights and gain a competitive advantage (Richey, Morgan, Lindsey-Hall, & Adams, 2016). For example, in the context of supply chain planning, big data could improve risk management by reducing exposure to various risks (e.g., the risk of fraud and other malfeasances). In the context of supply chain execution, big data may lead to increased efficiency and profitability by maximizing speed and visibility, improving supply chain relationships, and enhancing supply chain agility (Barratt, Sodero, & Jin, 2014; Uckelmann, Hamann, & Zschintzsch, 2009). Likewise, in the area of innovation, big data could support and enhance innovation (Diamantini, Genga, Potena, & Ribighini, 2014). Despite this evidence, some analysts argue that the deluge of data threatens to "break the existing data supply chain" (Lohr, 2012).

Looking to the past, we can find a substantial lack of papers specifically aimed at investigating the role of analytics in different supply chain processes. The few studies on this topic have mainly adopted a broader supply chain perspective and are still very preliminary. Some authors have investigated the potential benefits of social networks for supply chain management, mentioning inbound supply chain activities as one key area of investigation (Chae, 2015). Dutta and Bose (2015) analyze the phenomenon of big data by thoroughly investigating the characteristics of the cement industry supply chain, while other studies focus on using big data in supply chain management processes (Hazen et al., 2015) or on using big data to foster supply chain innovation (Tan et al., 2015).

A more comprehensive view is provided by Richey et al. (2016), who try to conceptualize the way in which big data can be used to support supply chain management processes in order to provide background for the term, its dimensions, and issues related to big data. They conclude that big data has four distinct dimensions (volume, velocity, variety, and veracity), and their success factors include better decision making,

Table 1
Summary of the literature

Reference	Business process	Tools	Data sources
Barratt et al., 2014	Retail supply chain	Not mentioned	Large datasets including data other than traditional transactional data
Chae, 2015	Sales and operations Planning	Analytical IT	Business analytics
Diamantini et al., 2014	Innovation management	Data mining	Electronic e-mails
Dutta & Bose, 2015	Product development, operations, and logistics	Not mentioned	Big data analytic projects
Hazen et al., 2015	Supply chain management	Analytical IT	Data science, predictive analytics, and big data
Richey et al., 2016	Supply chain management	Statistic approaches	Structured and unstructured data
Tan et al., 2015	Supply chain management	Deduction graph technique	Tweets, videos, click streams, and other unstructured sources
Uckelmann et al., 2009	Supply chain management	Not mentioned	RFId data

operational efficiency, data security, adequate storage, and transparency in partnerships. This evidence can be considered a reference for other supply chain research on the topic.

The main areas of big data that are investigated in the literature are reported in Table 1.

3. Research motivations and framework

3.1. Research questions

The fact that supply chain management literature on big data is still in its infancy is even clearer if we focus our attention on explorations of big data's ability to support the management of inbound supply chain activities (i.e., PSM).

Previous papers have described business intelligence methods and applications specifically tailored to procure departmental necessities. For example, authors have discussed data mining methods to classify suppliers or evaluate performance in order to select supply chain partners (Razi et al., 2014; Soloukdara & Parpanchi, 2015). Scholars have also investigated procurement practices, such as 1) negotiation strategy (Carbonneau, Kersten, & Vahidov, 2011; Carbonneau, Vahidov, & Kersten, 2014), 2) early identification of possible supply chain disruptions and risk sources that may affect sourcing activities (Chan, Samvedi, & Chung, 2015; Wang, Xie, Demers, & Gehrke, 2013), and 3) customer data evaluation in order to obtain useful insights into the relation between supply materials and items provided to customers (Zhang, Cui, & Wang, 2014).

However, despite isolated attempts to evaluate the role of analytics in procurement-related activities, the research on procurement analytics seems to be limited. This may sound strange, as the process of procurement has a lot in common with the process of marketing in terms of potential applications to big data, and many studies have investigated how big data and analytics can be used to enhance marketing activities (e.g., Linoff & Berry, 2011; Tirunillai & Tellis, 2014) and achieve benefits in the market (e.g., Arthur, 2013; Bottani, Montanari, & Romagnoli, 2016).

Procurement activities have disposed of structured data at different stages (such as supplier selection and supplier evaluation) for several years (Van Weele, 2004). For this reason, and in line with Carbonneau et al.'s (2014) suggestions, the procurement process could strongly benefit from the adoption of big data, and how this support can be conceptualized is a promising area of research.

For these reasons, we developed the present study around the following research question:

RQ1: How can big data support the procurement process?

Moreover, the literature has illustrated the potential benefits of big data for companies, particularly in managerial decisions. There are two main streams of such research. The first focuses on the impact of big data on performance, such as a firm's efficiency (Chae et al., 2013; Trkman, McCormack, Valadares de Oliveira, & Ladeira, 2010; Valadares de Oliveira, McCormack, & Trkman, 2012), supply chain promptness (Schoenherr & Pero, 2015; Vlachos, 2013), transparency (Dutta & Bose, 2015; Wamba et al., 2015), quality (Ma, Xiao, Xie, Li, Luo, & Tian, 2011), and productivity (Accenture, 2014). The second focuses on the benefits related to capabilities, such as support in defining strategies (Holsapple, Lee-Post, & Pakath, 2014; Wamba et al., 2015) and operational decisions (Holsapple et al., 2014; Vlachos, 2013), in creating informed processes (Holsapple et al., 2014), and in developing innovative business models and products (Wamba et al., 2015).

However, these measures are not specific to procurement. In order to motivate companies to introduce big data into the procurement process, the positive impact of big data on procurement performance should be emphasized, which has not yet been done.

Thus, we developed our second research question:

RQ2: How can adopting big data in the procurement process improve procurement performance?

3.2. Research framework

In order to answer the two research questions, we designed a research framework based on Laney's (2001) concept of the 3Vs (Volume, Velocity, Variety) and Richey et al.'s (2016) vision regarding big data in supply chain research.

If we look at past scholars' efforts to create a comprehensive classification of the features of big data, two main focus points emerge.

First, some authors mainly discuss the "format of data" used to perform analyses (Tan et al., 2015). Two main types of data are discussed (Connaughton & Sawchuk, 2014; Hu et al., 2014):

- *Structured data*, referring to all data that present a schema and so can be stored using a relational database model. This category includes all the internal and external data sources often stored in traditional enterprise data systems.

- *Unstructured data*, referring to all data that do not present a schema and cannot be stored in a traditional relational database. This category includes several sources of data, such as images, videos, social media content, newspaper, and web data.

Second, some authors address the "purpose" of using big data analytics (Zeng, Lin, & Xu, 2011). In that case as well, two main categories could be identified;

- *Reporting purpose* (Hahn et al., 2015; Rozados & Tjahjono, 2014; Zeng et al., 2011), or the aim to monitor one or more variables and report their evolution over time in order to describe how the business performed in a given period.
- *Predictive purpose* (Chae et al., 2013), or the aim to obtain insights into the future behavior of one or more data attributes.

The two aspects mentioned above are not independent, but interrelated, as represented in Fig. 1. The impact of big data features on procurement decisions has not yet been investigated, to the best of our knowledge. However, some authors have addressed the importance of considering those variables in more general supply chain decisions (e.g., Tan et al., 2015). The literature has specifically addressed the relevance of both structured and unstructured data with predictive purpose to risk management choices as well as planning decisions.

Assuming the procurement perspective, the unit of analysis for our investigation of big data usage is the procurement process. To provide an overall picture of the procurement process and answer RQ1, we identified the different phases of the procurement process based on the PSM literature.

Procurement can usually be defined as a process encompassing the identification and evaluation of user requirements, verification of suppliers' ability to meet these needs, development of agreements with those suppliers, implementation of ordering mechanisms, confirmation that payment occurs promptly, and evaluation of suppliers' performance, all of which are driven by a specific procurement strategy and objectives (Monczka, Handfield, Guinipero, & Patterson, 2010; Van Weele, 2009).

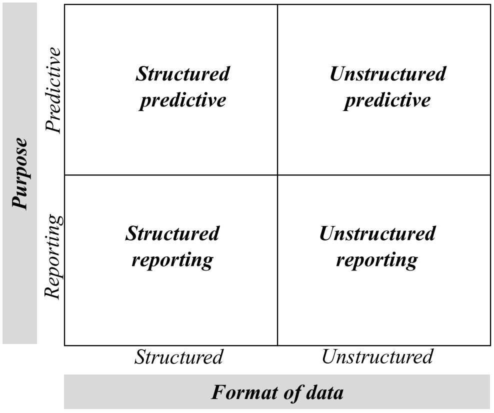

Fig. 1. Big data features.

A comprehensive view of the different phases of the procurement process is presented by Luzzini, Longoni, Moretto, Caniato, and Brun (2014), who distinguish between the following:

- *Strategic sourcing* (Chen, Paulraj, & Lado, 2005; Leenders, Fearon, Flynn, & Johnson, 2002; Monczka et al., 2010), which involves procurement strategic decisions such as the decision to make or buy a product, definition of general procurement policies, reverse marketing, spend analysis and portfolio approaches, and supplier relationship management.
- *Sourcing* (van Weele, 2009), which pertains to tactical choices such as definition of the specifications of products or services to purchase, requests for quotations, supplier evaluations, negotiation, and selection.
- *Supply* (van Weele, 2009), which pertains to operational activities such as order placement, expedition, receiving and control, invoice reconciliation, and payment. Planning activities related to production are not included in this phase.

In order to address the real value of using big data in different stages of the procurement process, the impact of big data on performance should be assessed as well, thereby answering RQ2. The literature has clearly addressed the potential value of jointly used structured and unstructured data with either reporting or predictive purpose in supply chain management to enhance performance. Chae et al. (2013) investigated the role of structured and unstructured data in enhancing efficiency. Vlachos (2013) mentioned the predictive role of big data (jointly structured and unstructured) to improve supply chain promptness, but did not find a clear link between procurement performance and big data. Recently, scholars have debated about the proper performance measurement system for procurement activity, which is important since procurement clearly impacts the overall results of a company. In particular, authors have addressed the need for strategic alignment of a company's procurement decisions and competitive priorities (e.g., Harland, Lamming, & Cousins, 1999; Nollet, Ponce, & Campbell, 2005). In order to measure the impact of procurement decisions, we used the model proposed by Caniato, Luzzini, and Ronchi (2014), which combines efficiency and effectiveness measures, adopting both an internal (i.e., company processes) and external (i.e., supplier) perspective. In this model, procurement performance is evaluated based on six categories: cost, time, quality, flexibility, innovation, and sustainability.

By combining the features of big data, the procurement process, and procurement performance, we obtain the overall research framework depicted in Fig. 2, which links the two research questions addressed by the study.

4. Research methodology

As the topic of our study is underdeveloped in the existing literature, we decided to adopt an exploratory design with multiple research methodologies to explore our research questions.

In particular, we decided to first run a focus group to investigate in depth the topic of big data adoption for supporting the procurement process and to better understand which phases of the procurement process may be impacted by these tools. Then, we used

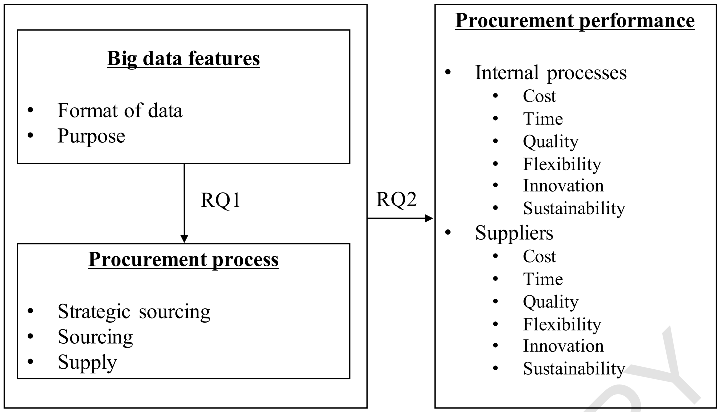

Fig. 2. Research framework.

exploratory case studies to address the real contribution of big data in the key phases of the procurement process as well as the possible benefits of improved procurement performance. Details about the focus group and the case study approach are presented in the following sections.

4.1. Focus group

The research framework in Fig. 2 was developed based on the literature review. Then, a focus group of 15 procurement experts was arranged to obtain their perspective on the topic and about the areas of the procurement process in which big data could provide valuable support. The focus group is considered an appropriate methodology to analyze new topics and facilitate brainstorming as it creates a collaborative and creative atmosphere (Barbour, 1999). Moreover, it has proved to be appropriate for acquiring direct feedback from experts (e.g., Andic, Yurt, & Baltacioglu, 2012). The 15 experts were all Chief Procurement Officers (CPOs) selected for their extensive experience with procurement and their interest in this topic. The sample included manufacturing companies, professional services, financial services, and construction companies. The companies were from different countries, and most of them were multinational. The focus group sample is summarized in Table 2.

The meeting lasted three hours and was conducted in such a way as to generate a natural, unrestricted discussion of the subject, which was observed and guided by the interviewers (Andic et al., 2012). In particular, the focus group was designed as follows:

1) Experts were asked to complete a structured questionnaire to collect their ideas about the topic.
2) A free, open discussion was moderated by two researchers.
3) The results of the questionnaire were reported to show the main impressions of the panel.

Table 2
Focus group sample

Number of employees		Turnover (Million €)		Industry		Headquarters	
Employees	% of companies	Turnover	% of companies	Type	% of companies	Country	% of companies
1–100	20%	0–49	27%	Construction	13%	Italy	40%
50–100	0%	50–249	20%	Manufacturing	33%	USA	27%
100–1000	27%	250–1,000	7%	Financial	13%	German	20%
1000–10.000	53%	>1,000	47%	Services	40%	Denmark	7%
						Spain	7%

4) Based on these data, a structured discussion was organized to understand the potential contribution of big data to the procurement process and which phases of the process were most improved.

4.2. *Case studies*

Based on the evidence obtained from the focus group, we decided to adopt a case-based methodology. Since qualitative case-based methodologies have often been considered the best way to proceed in the early, exploratory phases of research (Yin, 2003), this methodology has been chosen in this phase of the research to obtain an in-depth understanding of the choices of the investigated companies regarding big data and its support of the procurement process. Case-based research such as this provides new and creative insights, allows for the development of new theories, and has high validity among practitioners (Yin, 2003).

Multiple case studies were selected for theoretical replication (Leonard-Barton, 1990). In particular, following discussions during the focus group, we were able to identify the names of some multinational companies that had adopted big data in the procurement process. In order to be considered for interviews, we evaluated whether these companies adopted big data consistently for at least one of the 3Vs. This conservative approach was followed due to the low level of adoption of big data in the procurement department of all companies.

Companies that consistently fulfilled this criterion were contacted to participate in the research, and four of them accepted. Thus, we ran four exploratory case studies to investigate the main contribution of big data to the procurement process as well as evaluate the main impact on procurement performance. These companies were all medium-to-large corporations in different industries in which procurement plays a role in companies' strategies. In Table 3, the case study sample is summarized.

In each case, the unit of analysis was the procurement process. Data were collected in 2015 and 2016 through direct semi-structured interviews with the CPO and his/her team. Data were then triangulated with information collected from secondary sources (e.g., documents available on the Internet and provided by the company) to increase the construct validity (Eisenhardt, 1989). With the interviewee(s)' permission, the researchers recorded the interviews to prevent information loss, transcribed these recordings, and then integrated them into the notes taken during the interviews (Riege, 2003).

Table 3
Case study sample

Company	# of employees	Turnover (Mln €)	Industry	Headquarters	Big data perspective
A	155	22	Distribution	Italy	Volume, Velocity
B	6,307	1,900	ICT	USA	Volume, Velocity, Variety
C	900	3,000	Clothing	German	Volume
D	1,100	950	FMCG	German	Volume, Variety

Once collected, the data underwent within- and cross-case analysis. Each case was singularly investigated based by categorizing the level of adoption of big data, the phases of the procurement process that were improved by big data, the value generated for the company, and additional opportunities available to the company. Then, the cases were compared through cross-case analysis, addressing their main commonalities as well as differences in adoption and benefits.

5. Evidence regarding the impact of big data

Analysis of information collected from the focus group and the four case studies allows discussion of the nature of procurement activities, the effect of big data, and their practical contributions. Before presenting the main results of the cross-case analysis, we would like to present some technical considerations regarding the case studies. Most of the companies in our sample mentioned the need to take advantage of external consultants to learn how to analyze and use big data as well as facilitate in-depth training for those responsible for purchasing in order to increase their technical competency regarding measuring and reading data. Companies also used different sources of big data depending on their main needs, as discussed below. Some companies mentioned that structured quantitative data was already available in the company, several mentioned news about suppliers were already present, while others addressed tweets or other data on social networks.

5.1. Identification of the phases of the procurement process impacted by big data

Focus groups have allowed researchers to deeply investigate the role of big data analytics within the procurement process. One manager involved in the focus group mentioned the potential value of big data during the procurement process:

"Data have always been out there. Companies started to accumulate the data long ago, so the term 'big data' does not have a completely new meaning. However, in the last few years, the mentality of the buyer has changed; now he/she is aware of the fact that the data at his/her disposal can be employed in order to increase the efficiency of the procurement activity. In the past, due to a lack of technology, it was unthinkable to process the data. Today, it becomes possible, and several opportunities arise in the procurement process as well as in other departments."

Another CPO shared a different view than his colleagues. According to him, big data already play a vital role within the department, especially for multinational companies operating in manufacturing sectors:

"I am sure that the utility of big data in the procurement department has already been investigated, and big data analytics are already properly employed in most mature firms, especially those which are part of the manufacturing industry. Think, for instance, of the data from bills for materials in a firm that delivers thousands of different products. In the automotive industry, there are information systems able to trace all the purchased components and to monitor their location along the supply chain. In my view, these systems are clearly big data processors."

The CPOs also discussed the adoption of big data within the procurement process. They stated that big data may better support the procurement process but should not be extended to all types of procurement. Big data has the highest value for standard and indirect products, for which much information about the features of the market are publicly available. The focus group mentioned examples related to travel management, energy, and ICT purchases. Custom products and more strategic types of products are less impacted by big data.

In terms of format, the majority of companies preferred structured data. However, some companies had made preliminary attempts to use unstructured data gained through external sources in order to better invest in the procurement categories mentioned above.

Finally, the focus group highlighted which phases of the procurement process can be improved by the adoption of big data analytics. The panel experts mainly addressed the relevance of big data to strategic and tactical decisions. On the one hand, strategic decisions can be significantly improved by additional information as decisions can be made with a long-term perspective (for example, when dealing with defining a procurement strategy or analyzing spending). These results are consistent with previous studies, such as those of Soloukdara and Parpanchi (2015) and Razi et al. (2014). One CPO addressed the role of big data in reverse marketing, especially for global sourcing; big data allows companies to compare several options, including suppliers that are not an active part of the supply base.

The sourcing phase can be improved by deeper knowledge of suppliers' company features and performance. According to the experts, this phase is the one in which big data can have the highest impact, particularly concerning supplier evaluation, negotiation, and supplier selection. This result is consistent with existing literature (e.g., Carbonneau et al., 2014).

The experts also addressed the limited contribution of big data to the supply phase due to the typical operational nature of these activities. From an operational perspective, big data has no predictive advantage, and at the reporting level, its benefits are limited. However, the experts highlighted that this is the phase in which the majority of data to be used in the other phases are collected. For instance, if a supplier performs poorly in comparison with its competitors, this information will be used during the sourcing phase to support the selection of a vendor that allows companies to improve their performance.

In line with these considerations, we formulated the following proposition:

P1: Big data could support strategic sourcing in terms of procurement strategy and configuration, reverse marketing, and spend analysis as well as sourcing in terms of supplier evaluation, negotiation, and selection (Fig. 3).

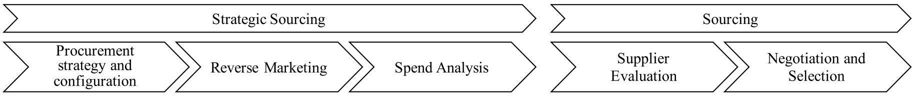

Fig. 3. Procurement process phases that can be improved by big data.

We decided to investigate only the "strategic sourcing" and "sourcing" phases of the procurement process during development of the exploratory case study. Based on the preliminary evidence, we decided to discard the "supply" phase.

5.2. *Identification of the contribution of big data to the procurement process*

Following Proposition 1, companies were interviewed in order to determine the actual contribution of big data to the strategic sourcing and sourcing phases. Annex 1 reports the main results of the cross-case analysis. The following sections present the main evidence.

5.2.1. *Strategic sourcing*

The case studies highlighted that big data has the highest potential value for strategic sourcing.

In terms of procurement strategy, company D noted the importance of sourcing planning and forecasting. Analytics can support identification of the best planning strategy to implement by using structured data such as bills of materials and price histories as well as unstructured data such as social media and web information. These decisions answer three questions: where, when, and how supplies should be obtained. The importance of analytics instruments increases exponentially with the number of variables that must be included in the planning activity. For instance, without the support of analytics, evaluating the best supply planning strategy for a product composed of several sub-components that can change over time may become an overwhelming task. Big data analysis might also identify correlations and trends among variables and the prices of goods and services. The price of business travel, for example, might be statistically correlated to the class of travel, route, airline, and number of days in advance the trip was booked. These analyses support the definition of specific travel policies based on statistical evidence. A similar approach might also be applied to the correlation between the price of components, services and utilities, and commodity prices, providing the opportunity for price hedging strategies.

Forecasting techniques have been developed to foresee market conditions and determine the likely outcome of incoming demands. They have rarely been adopted at other stages of the internal supply chain. However, they can be used in other departments, including the procurement department, especially for long-term decisions regarding procurement timing and quantity. Statistical methods can be widely employed to predict future economic conditions to inform strategic long-term decisions, such as the inventory of finished goods (Ketter, Colling, Gini, Gupta, & Schrater, 2012). New models aim to predict future supply forecasts using not only structured data but also unstructured data collected from the Internet and social media. For example, company B started collecting data from the web to inform supply forecasting for travel management, but it is also planning to investigate how unstructured data might be considered.

Several companies addressed the value of a risk management approach. Traditionally, risk management has been based on structured internal data generated by the firm, collected inside the ERP system, and made available to closest suppliers. However, an uncountable amount of potential sources of information are available through the Internet (e.g., sensors, newscasts, social networks). These sources can be paired with a traditional analytics framework to explore new ways to extract business value. The availability of new big data architectures has enabled the storage of a huge amount of data that could not be collected before due to management costs. Company A addressed the importance of using big data to incorporate sustainability and financial information into risk analysis. It adopted big data on the one hand to report actual situations in the supply base regarding financial stability and, on the other hand, to predict future situations. The company mentioned that significant investments in sustainability indicate financial stability, which is incorporated into predictive models of analysis. This result is consistent with the literature addressing the key role of big data in early detection of possible supply disruptions (e.g., Chan et al., 2015; Wang et al., 2013).

Another important area in which big data could have high value is reverse marketing. Company B utilizes data regarding the prices proposed by suppliers all over the world to make the best decision. Internally, they implemented a system similar to Booking.com's: based on big data, the system suggests the most convenient supplier for a specific procurement category. The purpose is twofold: to investigate existing suppliers and better understand how they are currently working and to determine the best available options, especially concerning efficiency and cost. The company addressed potential value not only from the perspective of price but also from the perspective of innovation. Through this system, they are able to detect opportunities for innovation concerning the most frequently purchased items and use this unstructured information to highlight the main trends in the market and consistently revise the supply base.

The third important area in which the adoption of big data analytics has notable potential is spending analysis in the procurement department. Concerning analysis of spending and review of costs, buyers must have control over spending, and know how much and with whom they are spending their money. Big data can support employees responsible for procurement by providing reporting tools that can segment spending and highlight how the amount of goods procured can be rationalized. For example, Company B adopted structured big data from a combination of internal and external sources of data for travel management. Through this analysis, before negotiating with suppliers, the company was able to identify problematic areas and fragmentation of spending among different suppliers. By rationalizing its spending, it was able to determine new practices to be implemented, with an expected savings of 6%.

Contract management can be improved as well, mainly through a better reporting approach. In the case of complex and burdensome contracts, procurement activity cannot be limited to the signature moment, but the agreed-upon conditions and expiry dates have to be continuously monitored in order to avoid disruptions that may have a huge impact on procurement performance and the company as a whole. Big data can provide information that is necessary to manage complex contracts. For example, company B used it to simultaneously compare conditions for complex contracts, thereby improving the management of internal processes.

5.2.2. Sourcing

Cross-case analysis identified the key contributions of big data analytics in the sourcing phase.

First, big data can support supplier evaluation by monitoring supplier performance. This result is consistent with the literature (e.g., Razi et al., 2014; Soloukdara & Parpanchi, 2015). Supply quality is usually assessed by internal controls for items received from the suppliers. However, random sampling is intended to guarantee the minimum standard and is only a proxy for the effective quality of the products. With the introduction of sensors for detecting specific product characteristics (e.g., temperature), it would be possible to implement tight quality controls. Moreover, in the last few years, companies have become more and more aware of the possibilities for generating value through the procurement department. One of these possibilities involves exploiting the company's relationship with its supplier in order to foster opportunities for innovation. When big data are employed within the procurement process, in other departments, the focus shifts from pattern recognition to outlier research. Indeed, the detection of opportunities for innovation is one case in which research about outliers can create value opportunities. In the past, company D adopted a vendor rating system for yearly supplier evaluation based primarily on structured data collected directly by suppliers. Recently, however, it introduced a pilot system that integrates data from external sources to complete the evaluation. Structured data with both reporting and predictive purposes are used, whereas only unstructured data with a reporting purpose collected through external sources were used in the previous system.

In terms of negotiation and selection, informative tools for determining negotiation strategies are some of the most powerful instruments at buyers' disposal during negotiation activities. The more valuable information that a buyer is able to collect about a supplier, the higher the buyer's bargaining power will be during the negotiation. The number of information sources has increased in the last few years, and consequently, the potential of big data has expanded. For example, company C stated that, nowadays, it is increasingly difficult to find areas with inefficiencies, so in order to find new ways to extract value from procurement, it is important to use additional information to better define the negotiation strategy. The last domain in which those responsible for procurement can rely on big data is supplier selection. When a company engages with a new supplier, every single piece of information about the supplier is important—not only figures from financial statements or other public data but also unstructured data, including newscasts, papers, social media posts, and information on the Internet, are valuable sources that should be surveyed. New technologies enable not only "hard analysis" of the operative and financial performance of suppliers but also evaluation of "soft" features, like reputation.

6. What is the role of big data in procurement?

Based on the results of our case studies, we were able to link the features of big data to the phases of the procurement process, as shown in Fig. 4. The figure addresses the critical role of structured data in supporting the procurement process. Procurement departments have used structured data for years to make their main decisions, and this source of information is still perceived as key. As expected, all the phases of the procurement process would benefit from the adoption of a large amount of structured data with both reporting and predictive purposes. Having structured data is highly relevant; the more data are structured (and perceived as reliable), the more can be used to manage relationships with external parties. In addition, for procurement, the availability of unstructured data from external sources is more limited than for other departments, such as marketing. For example, in business-to-business relationships, parties are less willing to share data publicly.

Some companies have made preliminary attempts to use unstructured data to support some phases of the procurement process. It has been adopted for a small number of procurement categories, either because a pilot approach to implementing big data is preferred or because unstructured data can be obtained more easily for some procurement categories. Indirect procurement, such as travel management, utilities, consumables, and maintenance services, is more impacted by big data than direct procurement of goods.

In answer to our first research question, the main results of this analysis can be summarized by the following propositions:

P2: The procurement process is mainly supported by structured data with either a reporting or predictive purpose.

P3: Unstructured data with either a reporting or predictive purpose support risk management, supplier performance monitoring, supplier negotiation, and supplier selection.

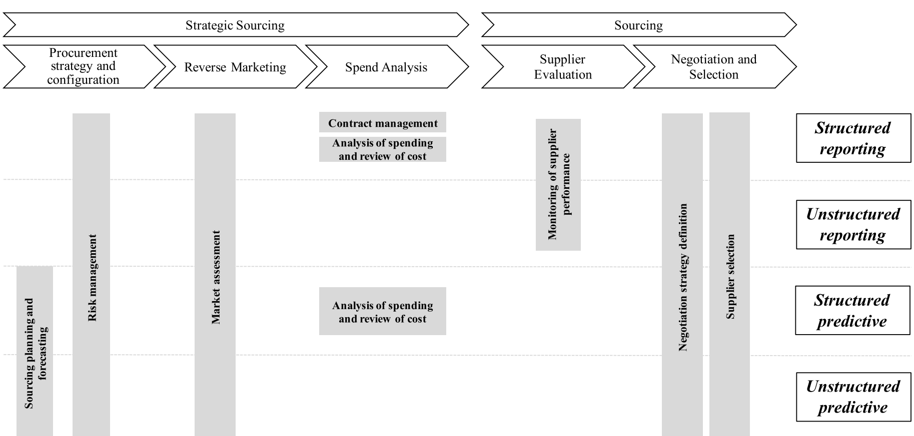

Fig. 4. Impact of big data on the phases of the procurement process.

P4: Unstructured data with a predictive purpose support sourcing planning and forecasting.

We can draw conclusions about the expected improvements in procurement performance after adoption of big data in the procurement process. Annex 2 and Table 4 report the main benefits for each phase of the procurement process.

The cross-case analysis shows that both internal processes and suppliers' performance are improved by the adoption of big data, although the main impact is on internal processes.

The main benefits for companies are related to cost and time. Due to the higher amount of available data, companies can make decisions more efficiently. However, it is not only a matter of efficiency; the quality of the procurement process might improve as well because more available information reduces the amount of errors that occur. Big data involves digital processes, documents, and data, which improves the overall reliability of the decision-making process, especially regarding contract management and supplier selection, as large amounts of information can be compared, reducing errors and increasing the quality of output. Moreover, in terms of risk management, improved ability to detect problems in the supply base increases the flexibility with which the procurement process can be managed, such as when looking for an alternative supplier or implementing a supply mitigation strategy.

Based on these considerations, we formulated Proposition 5 (which answers our second research question):

P5: Adoption of big data in the procurement process improves the performance of internal procurement in terms of cost and time and, consequently, its quality and flexibility.

Basing supplier selection, monitoring, and control on more data and information can also improve procurement performance at the supplier level. As mentioned above, the main benefit is cost reduction; however, better knowledge about the supply market and suppliers' cost structure leads to further negotiations and lower prices. In addition, big data available over the web or in other media allows companies to increase their scouting capabilities, thus leading to new—and, eventually, cheaper—opportunities in the supply market. Improvement in cost performance is the most cited benefit of big data in the sample; the companies introduced big data mainly for indirect types of procurement in order to improve efficiency and savings. However, today, procurement involves considerations other than savings. Suppliers are evaluated based on a wide spectrum of parameters, consistent with their strategic importance. Thereby, other types of performance might be improved, such as innovation potential, which is determined by reverse marketing and deeper monitoring of supplier performance, enabling identification of potential innovative processes.

Based on this evidence, we formulated Proposition 6:

P6: The adoption of big data in the procurement process improves suppliers' performance mainly in terms of cost but also potentially in terms of time, quality, innovation, flexibility, and sustainability.

Innovation and sustainability seem to be slightly or not at all improved by big data, according to the interviewed companies. This result could be explained by the

Table 4

Improvements in procurement performance due to big data

Phase	Activity	Practice	Procurement performance											
			Internal processes						Suppliers					
			C	T	Q	F	I	S	C	T	Q	F	I	S
Strategic sourcing	Procurement strategy configuration	Sourcing planning and forecasting	■	■					■					
		Risk management	■	■		■								
	Reverse marketing	Market assessment	■	■					■				■	
	Spend analysis	Analysis of spending and review of cost	■	■					■					
		Contract management	■	■	■									
Sourcing	Supplier evaluation	Monitoring of supplier performance	■	■					■		■		■	
	Negotiation and selection	Negotiation strategy definition	■	■					■					
		Supplier selection	■	■	■				■	■	■	■	■	■

still-limited adoption of big data in procurement departments, making these "advanced" performance indicators hard to detect.

In conclusion, it is important to address the drawbacks mentioned by some companies regarding the use of big data. Some companies addressed problems related to the technical competences needed to introduce big data. As mentioned above, most of the companies needed the support of external consultants to start using big data. Thus, companies must train employees to cope with big data once the consultants have finished their contracts or they must maintain a long-term relationship with the consultants. The second drawback that some companies mentioned was the difficulty of determining the weight of big data compared to the standard data used by companies. In other words, how much should, for example, a single piece of news affect the overall evaluation of a supplier? Given that traditional data are still used, the companies were unsure how to manage both traditional and new sources of data.

7. Conclusions

Data management is becoming more important every day, especially for business environments that base their competitive advantage on business intelligence skills. Big data is one of the most popular trends for data management in today's business context.

During the last few years, big data has radically changed the rules of business in data-based sectors (e.g., finance, B2C e-commerce), and it is now spreading to traditional industries as it has a huge potential to improve the way in which businesses are run. Through big data, company are able to interpret past and current trends and make predictions about the future based on countless information sources, which is especially helpful in sales and marketing activities, which rely on available consumer data.

Since these benefits are evident, several areas of companies have started to adopt big data, such as supply chain management; the possibility for mining huge amounts of data collected from disparate sources in real time can allow for a priceless competitive advantage. The literature about big data has primarily discussed its potential use in business and has touched the topic in a structured way, especially regarding its effect on procurement. Starting from this state-of-art, the present paper aims to identify the value of big data for procurement in terms of 1) the phases of the procurement process and 2) procurement performance. After analyzing the existing literature and the results of the focus group, we conclude that big data has the greatest potential impact on the strategic sourcing phase (mainly in terms of procurement strategy configuration, reverse marketing, and spend analysis) and the sourcing phase (mainly in terms of supplier evaluation, negotiation, and selection). These preliminary results were further investigated by four exploratory case studies, which analyzed in more depth each phase of the procurement process, using examples of big data implementation in real situations.

Based on the results, we conclude that big data could affect the procurement process differently in different formats:

- In a structured form, big data with either a reporting or predictive purpose has an impact on all strategic and sourcing activities.

- In an unstructured form, big data with either a reporting or predictive purpose has an impact on risk management, supplier performance monitoring, supplier negotiation, and selection, while only data with a predictive purpose has an impact on sourcing planning and forecasting.

Cross-case analysis enabled us to identify the main impact of big data adoption on procurement performance. We used a twofold perspective, looking at both the internal procurement process and supplier performance metrics. This comparison highlighted the impact of big data adoption on the procurement process, first in terms of cost and time and subsequently in terms of quality and flexibility. Moreover, the evidence shows that big data improves suppliers' performance mainly in terms of cost but also potentially in terms of time, quality, innovation, flexibility, and sustainability.

Overall, this paper presents exploratory research in a new area of investigation within PSM literature. Although exploratory, our study contributes to both research and practice. In terms of research, it represents the first attempt to empirically investigate big data adoption within companies' procurement departments, combining literature on both procurement and big data. With our results, we fill two main gaps in the literature; on the one hand, we identify which phases of the procurement process might be impacted by big data, and on the other, we investigate the practical impact of big data on procurement performance. Moreover, as previous research is mainly theoretical, this paper supports past findings with empirical evidence on the topic performed using multiple methodologies (a focus group to collect experts' opinions and exploratory case studies to identify companies' best practices). Finally, the paper presents six research propositions that can be tested in future studies, thus driving further research on the impact of big data on procurement. In terms of practical implications, big data are a hot topic among managers today, and they need support to understand big data's possible applications in supply chain (and procurement) management. This paper identifies key procurement activities in which procurement professionals could utilize big data to improve performance. Moreover, this research helps managers identify which format of big data (i.e., structured or not structured) should be used in which phase of the procurement process.

The paper also has some limitations that can be overcome in further research. Additional research should aim to increase empirical research on the topic, perhaps with an action-based approach or through longitudinal case studies, in order to understand the horizontal implementation process of big data in different procurement departments. Further, the current paper is strongly focused on big data's managerial impact on those responsible for procurement, thus partially neglecting the technological perspective. Subsequent studies should investigate the technological aspects of big data, such as the role of tools in the processing of big data in analysis. Finally, a statistical sample, perhaps at the international level, should be used to test the research propositions in this paper to address their validity, both in terms of the adoption of big data in the procurement process and the impact on procurement performance.

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Annex 1 Cross-case analysis

		Company A	Company B	Company C	Company D
Strategic sourcing	Procurement strategy configuration	Assessment of supplier's risk in terms of financial performance and sustainability	Integrated supply risk and value management by anticipating disruptions Supply forecasting		Sourcing planning in order to simplify the supply base Assessment of supplier's financial risk
	Reverse marketing		Market assessment Detection of new innovative opportunities		
	Spending analysis		Historical price analysis of spending and review of costs Comparison of several contract conditions for improving contract management	Analysis of spending and review of costs by comparing suppliers based on structured and unstructured data Performance measurement for strategic suppliers	Performance measurement for strategic suppliers
Sourcing	Supplier evaluation		Monitoring of supplier performance	Continuous monitoring of quality and innovation	Monitoring of supplier performance, especially working capital management
	Negotiation and selection		Processing data about more frequently bought items to address negotiation efforts and define a negotiation strategy based on more information. Support optimal supplier selection	Support definition of a negotiation strategy based on more information Use large volumes of data to make supplier evaluation and selection more structured and reliable	

Annex 2 Impact on procurement performance (in brackets, the reference to the company case)

Phase	Activity	Practice	Procurement performance		Description
			Internal processes	Suppliers	
Strategic sourcing	Procurement strategy configuration	Sourcing planning and forecasting	Cost (B, D) Time (B)	Cost (B)	Hedging strategy formulation, more efficient management of the procurement process and helping the supplier reduce costs, with a decrease in internal data cost management
		Risk management	Cost (B, D) Time (B, D) Flexibility (A, B, D)	–	Minimization of supply risk costs, anticipation and detection of supply chain disruptions, more flexibility due to a more reactive process
	Reverse marketing	Market assessment	Cost (B) Time (B)	Cost (B) Innovation (B)	More efficient market assessment, leading to the selection of more efficient and more innovative suppliers
	Spend analysis	Analysis of spending and review of cost	Cost (B) Time (B, C)	Cost (B, C)	More efficient management of internal processes with a with a decrease in internal data cost management; achievement of savings for the supplier by detecting opportunities for savings
		Contract management	Cost (B) Time (B) Quality (B)	–	Early detection of contract issues, reduced time and cost needed to analyze contracts, reduction in contract errors, improvement in contract quality
Sourcing	Supplier evaluation	Monitoring of supplier performance	Cost (B, D) Time (B, D)	Cost (B, D) Quality (C) Innovation (C)	More efficient process of supplier monitoring, improved supplier performance in terms of cost, quality, and innovation (likely, other types of performance as well)
	Negotiation and selection	Negotiation strategy definition	Cost (B, C) Time (B, C)	Cost (B, C)	More efficient negotiation and definition of strategies, acquisition of leverage in negotiations, achievement of savings
		Supplier selection	Cost (B, C) Time (B, C) Quality (C)	Cost (B, C) Quality (B, C) Time (B, C) Flexibility (B, C) Innovation (B, C) Sustainability (B, C)	More efficient and reliable supplier selection, identification of the best supplier for the specific type of performance investigated