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BIG DATA IN PROCUREMENT: THE ROLE OF PEOPLE BEHAVIOR AND ORGANIZATION ALIGNMENT[i]

GRANDES DATOS EN LAS COMPRAS: EL PAPEL DEL COMPORTAMIENTO DE LAS PERSONAS Y LA ALINEACIÓN DE LA ORGANIZACIÓN

BIG DATA EM COMPRAS: O PAPEL DO COMPORTAMENTO DE PESSOAS E ALINHAMENTO DA ORGANIZAÇÃO

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Citation

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Abstract

Complex and big data analytics attract growing interest in procurement strategies due to the possibility of decreasing complexity, lower costs, support assertive decision-making process and avoid fraud. This paper aims to exploit the role of organizational alignment and people's behavior on big data initiatives in procurement. Through a survey, the results suggest that to succeed, organization and procurement strategies must be aligned and the key driver to advance is cost reduction and the willingness to use new technologies. Although behaviors are relevant in management processes, the buyer's current behaviors do not significantly impact on the deployment of big data strategies. Keywords: survey, big data, strategic sourcing.

Resumen

Los análisis de datos complejos y big data atraen un interés creciente en las estrategias de adquisición debido a la posibilidad de disminuir la complejidad, reducir los costos, respaldar el proceso efectivo de toma de decisiones y evitar el fraude. Este articulo tiene como objetivo explorar el papel del alineamiento de la organización y el comportamiento de las personas en las iniciativas de Big Data en adquisiciones. A partir de encuesta, los resultados sugieren que, para tener éxito, las estrategias de organización y adquisición deben alinearse y el factor principal para avanzar es la reducción de costos y la disposición para utilizar nuevas tecnologías. Aunque los comportamientos son relevantes en los procesos de gestión, los comportamientos actuales del comprador no tienen un impacto significativo en el despliegue de estrategias de big data. Palabras clave: encuesta, grandes datos, compras estratégicas.

Resumo

Análises complexas e de big data atraem um interesse crescente em estratégias de aquisição devido à possibilidade de diminuir a complexidade, reduzir custos, apoiar processos assertivos de tomada de decisão e evitar fraudes. Este artigo visa explorar o papel do alinhamento da organização e do comportamento dos executivos nas iniciativas de Big Data no setor de Compras. Por meio de uma pesquisa, os resultados sugerem que, para ter sucesso, as estratégias de organização e aquisição devem estar alinhadas e o principal impulsionador para o avanço é a redução de custos e a disposição em usar novas tecnologias. Embora os comportamentos sejam relevantes nos processos de gerenciamento, os comportamentos atuais do comprador não afetam significativamente a implantação de estratégias de Big Data. Palavras-chave: survey, big data, compras estratégicas.

INTRODUCTION

Traditionally, procurement value lies in cost reduction, through tactics and competitive contracting (González-Benito, 2007; van Weele & van Raaji, 2014) and a growing number of studies have been demonstrating the need for moving forward to a clear value proposition strategy (Hong & Kwong, 2012; Chick & Handfield, 2015; Lilien, 2016). Procurement has been shifting its tactical role to a core element for strategy and competitiveness of organizations (Palraj et al., 2006; Tassabehji & Moorhouse, 2008). Most operational activities are already being rapidly digitized (Arnold et al., 2005; Hong & Kwon, 2012; Nicoletti, 2013) to support or substitute procurement operational tasks and it leaves free time for the development of more strategic action (Presutti Jr, 2003; Bendoly & Schoenherr, 2005; Wang et al., 2016). In this sense, technology in procurement activities is a way to connect and shift relationships (Gebauer & Segev, 2001, Cuganesan & Lee, 2006), achieve cost efficiency by optimizing process (Arnold et al., 2005; Hong & Kwong, 2012), exploit the procurement roles (e.g. Gadde & Håkansson, 1994; Tassabehji & Moorhouse, 2008) and enhance skills and capabilities (Carr & Smeltzer, 2000; González-Benito, 2007). It opens the doors to new organizational configurations and analysis (Nollet & Beaulieu, 2010) by requiring procurement and organizational integration and alignment (Ellram & Carr, 1984; Carr & Pearson, 2002; Pohl & Förstl, 2011; Ateş et al., 2018), through the identification and translation of business competitive priorities to clear procurement actions to fit business strategy continuously (Narasimhan & Das, 2001, Gonzalez-Benito, 2007).

However, the size, variety, and speed of data that impact procurement decision-making are expanding fast, and, the more strategical procurement became higher the demand for taking real-time assertive decisions. The evaluation of big and complex data in deep offers unprecedented opportunities for advancing in procurement value-adding, lower costs (Chae et al., 2014; Wang et al, 2016) and avoid fraud (Ramamoorti & Curtis, 2003; Westerski et al, 2015). On the other side, practitioners need to discern and act fast (Chick & Handfield, 2004), avoid premature design, share and take improper conclusions (Van Knippenberg et al., 2015; Bendoly, 2016). It requires investments in technology, organizational process change (Barbosa et al., 2018) as well as strategies and specific capabilities to handle and transform such huge amount of information into clear, reliable and valuable material to leverage resources (Tippins & Sohi, 2003; Kiron & Shockley, 2011; Carrillo, 2017).

Despite the strong interest of big data in supply chain and procurement strategies (e.g. Chen et al, 2012; Waller & Fawcet, 2013; Sanders, 2014; Li et al., 2016; Kache & Seuring, 2017; Gunasekaran et al., 2017; Roßmann et al., 2018), theoretical and empirical evidences of how to include big data strategies into procurement managers decision- making process still lacks (Mogre et al., 2017). Based on that, this study intends to verify: 1. To what extent do alignment, knowledge, and coordination of big data strategies impact its use and efficiency in the procurement environment? 2. Do current procurement executives' behaviors (intention and reaction of individuals) impact the deployment of data analytics and consequently the overall superior results?

To address these questions, we structure our paper as follows: First, we review some work exploring the integration between corporate, procurement and big data analytics strategy, followed by the role of procurers' behavior (intentions, actions, and reactions) that should influence the deployment of data analytics. Then, we present the methodology and data analysis. We conclude by discussing the implications of our findings and propose possible future studies for advancing this discussion.

INTEGRATION OF BUSINESS, PROCUREMENT, AND BIG DATA ANALYTICS STRATEGIES

"In the coming years, most intelligent organizations will need to blend technology-enabled insights with a sophisticated understanding of human judgment, reasoning, and choice. Those that do it successfully will have an advantage over their rivals." (Schoemaker & Tedlock, 2017, p. 27)

It is well discussed in the literature that, to succeed, Procurement must be aligned to corporate strategy (e.g. Watts at al., 1995; Narasimhan & Carter, 1998; Knudsen, 2003; Gonzalez-Benito, 2007; Baier et al, 2008). As Ellram & Carr (1984) state "Purchasing must assume a proactive role in working with other functions to formulate and implement competitive strategy, to minimize barriers between purchasing and other functions" (p. 8). The alignment facilitates procurement execution, it converts into better performance (Rodríguez-Escobar & González-Benito, 2017) and strength its recognition (Carr & Smeltzer, 1997). In fact, a growing comprehension of the strategic role of procurement in contributing to competitive advantage (Carr & Pearson, 2002) has drawn the attention of organizations to advance the alignment of corporate and procurement strategy.

Speed on decision-making is a critical issue for organizations and it is based on reliable and prevailing information. An organization must understand how to create, transform, and use the information to build a coherent view of a process, technology, and resource management (Choo, 1996). However, information is becoming obsolete fast. Therefore, the faster an organization manages to use real-time information, the greater its conditions for making more assertive decisions (Eisenhardt, 1989).

In this sense, big data concept is presented as a set of techniques and technologies that require new forms of integration to uncover large hidden values from large data sets that are diverse, complex, and of a massive scale (Hashem et. al, 2015). It is not a matter of how to store or access data, but how to analyze it to make sense and exploit their value (Bello-Orgaz et al, 2016). Waller & Fawcett (2013) intensify the idea of data science by coupling available and high-quality data and apply quantitative and qualitative methods to solve relevant problems in the field and forecast more assertive outcomes. Provost and Fawcett (2013) explain that data-driven decision is the way that one takes decisions based on data analysis rather than intuition or feelings.

The key challenge of procurement executives is how to deal with complex data, how to predict paths (Schoenherr & Speier-Pero, 2015) and, consequently, how to move forward incorporating big data analytics strategies into procurement decision-making (Waller & Fawcett, 2013). To support a superior appraisal of data dynamics and consequently leverage consistent decisions, organizations need to put efforts on the strengths of human and technology roles and for doing so, it demands a deep understanding of human judgment and technology capabilities (Schoemaker & Tetlock, 2017).

Recent researches point to the relevance to advance and align data analytics strategies to the overall business strategy of the organization (e.g. Agarwal & Dhar, 2014; Akter et al., 2016; Gunasekaran et al., 2017). The alignment between corporate strategy, procurement strategy and big data depends on the influence of top management (Gunasekaran et al., 2017) that synchronize interdepartmental competencies with the firm's strategic objectives (Akter et al., 2016), resolve conflicts of interest and address the sense of urgency (Kayser at al., 2018). In this sense, organizations need to develop an integrated model of analytics strategy that comprises the exploitation of internal data combined with external data sources, which includes environmental dynamics and its supply chain members' information (Sanders, 2014). However, according to Castells (2011), new technologies, when transforming the processes of information processing, act on all domains of human activity and enable the establishment of new connections between its elements and people. A virtuous circle of organizational transformation arises influencing the productivity and the efficiency of the institutions and consequently emerge new technological paradigms for the management.

It can also be observed in procurement dynamics. In line with Castells' observations, Sanders (2014) affirms that, for the success of big data exploitation in the Supply chain (and Procurement as well), organizations need to reconfigure process, technology, and people behavior. It includes the need to comprehend the impact of individual values, behaviors and social rules that underpin the current decision-making process. People, technology and process are fundamental parts for procurement transformation. Firstly, information is recognized as raw material, while new technologies act on information. Secondly, while information is part of the entire human activity, processes are shaped by the new technological environment. Consequently, these dynamics demand a clear observation of the logics established by networks, upon the increasing complexity of interaction, speed, and variability above human cognitive comprehension of the phenomenon as well as human behavior (Castells, 2011).

Due to its complexity, big data cannot be used as a direct input on decision-making. It must be interpreted, and traditional tools should be insufficient to handle such a miscellaneous of data (Constantinou and Kallinikos, 2015). This perspective does not diminish the need for human value, on the contrary, it contributes to a better analysis of data in a broader way, which, possibly, a buyer would not have enough cognitive capacity to analyze such complexity of data interrelationships. Thus, organizations need capable people, in terms of programming, data analysis as well as the comprehension of organizational policies and business environment (Arkter et al., 2016; Carrillo, 2017; Barbosa et al., 2018). According to McAffee & Brynjolfsson (2012), teams tend to set decisions more clearly aligned to objectives, ask the right questions, and consequently are more able to bring the most assertive answers to the challenges posed. This knowledge allows people to clarify terms, issues and possible results gain support to undertake speculative appraisal of data analytics (Braganza et al., 2017), which supports organizations to plan and control strategies (Arkter et al., 2016) by creating a "trail of evidence" (Braganza et al., 2017), avoiding maverick buying. This approach implies a significant structure change (Barbosa et al., 2018) and consequently demands management commitment to support continuous improvements over time.

Hypothesis 1: Management alignment, knowledge and coordination of technology strategies impact big data deployment on the procurement environment.

THE MICRO FOUNDATIONS OF EXECUTIVES' BEHAVIOUR: INTENTION AND REACTION

From the emergent opportunity for adding value from the abundance of data, challenges for management arise. It includes individual cognitive, social and motivational issues that are related to jeopardized decision-making (Van Knippenberg et al., 2015). Scholars highlight the relevance of individual behavior during an intervention in operations management (Gino & Pisano, 2008). Boudreau et al. (2003) mind to considering both technical and human aspects while investigating any changes in operating systems. It is discussed that the success of the implementation of tools and techniques in the supply chain field relies on human behavior. Individual behaviors, like lack of trust or risk aversion, tangle the initiatives to provide changes in operations management (Bendoly et al., 2006).

Environmental characteristics, organization rules, internal demands, and procedures influence the purchaser's behavior (Johnston & Lewin, 1996), as well as, a background of individuals, information source, perception distortion and satisfaction with past purchases (Sheth, 1973). Purchasers are under significant stress to achieve targets (Giunipero & Pearcy, 2000; Tassabehji & Moorhouse, 2008). When clear information lacks about the expectation associated with the order, the methods for fulfilling known procurement expectations or the consequences of individual performance (Johnston & Lewin, 1996) procurers' self-esteem and behavior are impacted. It is not rare to identify misunderstanding between purchasers' role self-perception and the organization's perception of its role (Tassabehji & Moorhouse, 2008). All these aspects drive procurers' decision-making mental orientation for making a purchase.

Hypothesis 2: Procurers' behaviors impact the deployment of big data analytics strategies on the procurement environment.

To better elucidate procurers' behavior that should influence the deployment of data analytics, we exploit hypothesis 2 in a deeper detail based on behavioral assumptions intentions, actions, and reactions (Bendoly et al., 2005).

Procurers intentions

Intentions refer to an internal orientation, a conscious formulated plan (Venkatesh et al., 2006) in reflecting a situational demand (Maruping et al., 2017) and the actual goals of the decision-makers (Bendoly et al., 2006). Particularly in procurement activities, efficiency is related to procurement competitive priorities cost, quality and innovation, which represent the major outcomes from procurement excellence (Naransinham & Carter, 1998; Baier et al., 2008). To become strategic indeed, the procurement executive needs to possess a strong set of skills, from technical, relational, market-oriented till achieve a strategic perception of value add (Tassabehji & Moorhouse, 2008). So, we include this mature capability as a competitive priority in line with the promised result of the adoption of big data.

The purchasers' core focus is on optimizing costs. It comprises the ability to search for alternatives of the best price for a product or service, decrease the unit prices of purchased items, reducing the total cost of ownership (Carter & Narasinham, 1996; Terpend et al., 2011) and improving cost efficiency. Price is one of the most important transaction components key elements of the true cost of purchase (Ellram, we translated the procurement competitive priority cost into procurement intention "best price seeking". Big data analytics is recognized as an important path for supporting managers to comprehend a broader picture of the market and by optimizing total cost (Chae et al., 2014; Wang et al, 2016).

Hypothesis 2a: Procurers intention of better price seeking impact on the deployment of big data analytics strategies on procurement environment.

The second procurement competitive priority and, consequently, procurement intention is "quality". Perceived quality is the buyer's judgment about products' overall excellence or superiority (e.g. Zeithaml, 1988). Purchasers with high skill levels and knowledge tend to look carefully at the quality (Cousins et al., 2006) and comprehend that the relationship price-quality is product specific (Gerstner, 1985). Additionally, it underlies individual psychological insecurity, an internal constraint imposed by previous orders or based on the uniqueness of the technology, material or service. Procurement practitioners can establish a correlation between brand and quality and become brand loyal because of the trust established with the supplier and the reputation perceived. Due to the abundance of information and cognitive biases of interpreting it, the organization shall be blind faith to the market and became satisfied with the brand (Walsh & Mitchel, 2008).

Hypothesis 2b: Procurers' intentions of better-quality seeking impact on the deployment of big data analytics strategies on the procurement environment.

Value has several meanings at the buyer's perspective (Zeithalm, 1988). At B2B view, value expresses is the worth the full performance of a product or service in monetary terms (Anderson et al, 2003). Understand how to transpose a better price seeking and quality view into the value-adding view is not an easy task (González-Benito, 2007; van Weele & van Raaji, 2014). A blended comprehension of both competitive priorities "cost" and "quality" drives for a higher-level priority and reflects the strategic business skills of the executive named value-added. In this level, procurement professionals intend to comprehend and observe how they can impact on overall business value (Tassabehji & Moorhouse, 2008). Their concern refers to find the best value for the money and looking for the very best choice, to observe if current suppliers are adequate for the current business needs and identify new forms to advance business with current suppliers as well as identify new supply alternatives in the market. The value of predictive information supports procurement executives to analyze and understand the market dynamics in several ways, faster and in real-time (Chick & Handfield, 2015).

Hypothesis 2c: Procurers' intentions of advancing value-adding business impact on the deployment of big data analytics strategies on procurement environment.

Finally, the last procurement of competitive priority is innovation. In the context of the present study we constraint innovation as the willingness to use new technologies due to the disruptive character of the process, relationships, and scope of procurement analysis. It is reasonable to infer that big data analytics shall grasp procurers' attention if they perceive it as useful for advancing their current challenges and it is easy to use. However, given the limited experience with technologies, peoples' intentions would not be expected to be well-formed and stable (Davis et al., 1989).

Hypothesis 2d: Procurers' willingness to use new technologies impact on the deployment of big data analytics strategies on procurement environment.

Actions and Reactions of Procurers facing the vastness of data

Actions refer to the implicit behavior of social actors in the environment. Actions tend to be inherent in the problems faced by executives and it comprises individual attributes such as cognitive limitations, motivation, ability to understand feedback and change, and communication. On the other hand, reactions are an individual response to a social change (Bendoly et al., 2016).

Currently, procurers are immersed in a vastness of data. A common reaction of procurers is the possibility to be confused by overchoice. It relies on the "difficulty when confronted with more product information and alternatives than they can process in order to get to know, to compare and to comprehend alternatives" (Walsh et al., 2007, p. 704). Despite procurers have more information, products and suppliers' alternatives, due to limited cognitive skill, they fall short to take fast decisions, and consequently they feel anxious (Malhotra, 1984; Walsh & Mitchel, 2008) and, not rare, reduces the quality of their decisions (Gari & Pisano, 2008).

Facing similar situation, overchoice-confused executives tend to interrupt decision making, seeking for additional information that should support the decision or narrowing down the set of information, by reducing the number of attributes to evaluate (Mitchel et al., 2005). However, most of the cases procurer are not able to postpone the order due to internal time-pressure. In that sense, procurement executives shall feel constrained and react negatively to any innovation in place or should understand data analytics as to the light at the end of the tunnel.

Hypothesis 3a: Confused by overchoicing procurers are the willingness to support the deployment of big data analytics strategies on procurement environment

Consequently, confused purchasers shall experience a reduction of their self-confidence for taking decisions. This insecurity of decision-making is mitigated by the possibility to share the decision-making asking people for pieces of advice (Walsh et al, 2008) or delegate completely the procurement decision (Mitchel et al., 2005). It can cause situations or sensations of lack of autonomy over time. It should be the case of capable purchasers that have enough skills but lacks organizational support and internal recognition of the full impact of procurement role or underdeveloped purchasers that requires mature skills for addressing her/his role (Tassabehji & Moorhouse, 2008). The trade-off time-pressure and high volume of data for decision-making shall lead procurers for the abandonment of the decision-making process (Mitchel et. al, 2005). In another side, there is a continuous search of procurers to be recognized by organization as an important role to support business success (Carr & Smeltzer, 1997; Tassabehji & Moorhouse, 2008), and data analytics is known as a key driver to support decision-making process as well as demands for a faster pace for action.

Hypothesis 3b: Insecurity of decision-making has a positive impact on the deployment of big data analytics strategies on procurement environment

Hypothesis 3c: Lack of autonomy reaction has a positive impact on the deployment of big data analytics strategies on procurement environment

Another reaction is the resistance to change suppliers or brands. Seminal studies of buyer behaviors suggested that loyalty is a relational phenomenon by comprising a purposive preferential behavior toward more competing alternatives (Jacoby & Kyner, 1973). Procurers may not be willing to experience a negative consequence of a possible fault of not being able to collect enough data and evaluating new suppliers or brands (Mitchel et. al, 2005). However, it should also be a result of personnel's desire to maintain relationships with established but unapproved suppliers (Kulp et al, 2006) due to friendship (Londsdale & Watson, 2005) or unethical behavior (Badenhorst, 1994). In this sense, big data analytics is an important initiative to identify Maverick buying (Karjalainen et al, 2009), non-purposive mistakes or even frauds (Ramamoorti & Curtis, 2003; Westerski et al., 2015).

Hypothesis 3d: Procurers' resistance to change suppliers impact negatively big data analytics strategies on the procurement environment.

Finally, in some cases, procurers are constraint by rigid specification, the pressure of internal clients to keep specific brands due to personal preference (Cox, 2005) or because qualified brand assigns symbolic meanings to product labels and attributes (Awanis et al., 2017). In such a situation, there is no alternative but to focus attention on specifications rather than any flexibility or opportunity one may find along the way. Procurers aim to make sure that the specifications or requisitions are met properly. Requirements shall restrict the exploration of opportunities to find better alternatives to the organization. This rigidity translates into inflexible behavior. It is reasonable to infer that procurers cannot perceive the usefulness of big data and do not support its deployment within the organization.

Hypothesis 3e: Procurers constrained by rigid specification or brand definition by others impact negatively big data analytics strategies on the procurement environment.

RESEARCH METHODOLOGY

The research methodology adopted by this study is the survey (Forza, 2002). The survey design comprises single-respondent research (Montabon et al., 2018) who answer all items, including both the independent and dependent variables. It is a monadic study (focus on a single perspective). Once the core focus of this study is behavioral and drives this attention to the individual decision-making process, the potential for respondent bias is lower (Flynn et al., 2018).

Survey design, construct measurement and questionnaire development

The questionnaire is constituted by 52 items grouped into 13 dimensions (as presented in Appendix A). Firstly, we evaluate big data capabilities and we measure "big data knowledge and strategy alignment" (8 items), "Planning and Control" (6) and "Coordination" (4) based on previous studies of Kim et al (2012), Byrd et al (2000) and Arkater et al (2016). Considering individual intention, we measure "best price seeking" (2), "Specification and brand seeking" (2), "Quality seeking" (3), based on Awanis et al. (2017), "Value proposition" (4) from Chick & Handfield (2004) and "willingness to use new technologies" (2), based on Davis et al., (1989) and Schoenherr & Speier-Pero (2015). The dimensions related to individual reactions were "confused by overchoice" (4), "lack of autonomy" (2) and "resistance to change suppliers" (5), were adapted by Mitchel et al., (2005), Walsh et al. (2007) and Walsh & Mitchell (2008) studies.

The key dependent variable used in this study is "Outcomes" that captures a practitioner's perception of procurement effectiveness by using complex data analytics. Based on Caniato et al. (2014) "Outcomes" is a second-order construct that comprises 7 items: The perception of executives that by using complex data analytics improved overall suppliers' performance, delivery accuracy, cost reduction, risks mitigation, internal customer response speed, predictability and planning and, governance.

All the items had answer choice ranging from 1 – Disagree Completely to 5 – Agree Completely. Beyond that, the questionnaire includes questions regarded to the characteristics of both managers and firms, such as gender, scholar degree, company size, and industry.

Sample and Data collection

The population chosen for this study was procurement professionals (van Weekly & Raaji, 2014) once they are knowledgeable informants (Ernst & Eichert, 1998). Data were collected by promoting the survey on social media (LinkedIn). The original network of researchers comprised about 7,500 executives. Firstly, we filter the database by selecting only Procurement professionals (about 850 executives). To mitigate the potential weakness of online survey as misperception of junk mail, unclear answering instructions, impersonal and low response rates (Evans & Mathur, 2005), we sent an individual message to each potential respondent. We present the main objective of the research as well as the importance of getting real figures of the current practices of strategic sourcing, relying on the relevance and lack of data concerning the role and value of procurement for organizations. We also asked if they perceived they are knowledgeable enough to attend the survey. Additionally, we attached the Survey Monkey link of the questionnaire to the message (Buchanan & Hvizdak, 2009). To increase the incentives of the participation we offer informants a summary of the findings. The data collection strategy adopted by this study was successful by increasing respondent involvement (Forza, 2002), narrowing to knowledgeable practitioners (Ernst & Eichert, 1998; Montabon et., al, 2018), and providing convenience for the respondent considering time and confidentiality (Bell & Bryman, 2007). Moreover, it favored the possibility to optimize costs for researchers and other resources constrain accessing geographical distant informants. We got responses from 270 Procurement Managers, however, 51 had more than 5% of missing values (from 20% to 75%). Those were eliminated from the dataset. Four managers had less than 5% and to them, we replace the missing values by the mean of the variable. At last, the sample is compounded by 219 informants (25,8% return rate).

Measure validation

The data were imported to statistical software SPSS vs. 22 to proceed with the analysis. The first step of analysis consisted of refining the dimensions through Confirmatory Factorial Analysis (CFA), which means that all items with a factorial load lower than 0,70 and significantly higher than 0,05 were eliminated from the analysis. After that, coefficients of reliabilities were calculated to verify the internal consistency of dimensions. It was used the Cronbach' Alpha, Composite Reliability and Average Variance Extracted (AVE). The last one should be higher than 0,5 while the others higher than 0,7 to endorse internal consistency.

The dimensions were converted into variables by estimating their factorial score through the Promax extraction method. The variables were used to test the relationship between Big Data usage and Procurement Capabilities dimensions on Procurement Outcomes, using Linear Regression. It was considered significant the relations between independent and dependent variables in which the significance was lower than 0,05.

RESULTS

First, we sought to understand the characteristics of the survey sample. It's constituted by 219 Procurement professionals, with the following scholarship: MBA (63,1%), bachelor's degree (31,3%), Master (3,2%), High School (1,8%) and Ph.D. (0,5%). The executives are from several industries as Automotive (20,74%), Services (17,51%), Chemistry and Pharmaceutical (14,75%), Food (11,52%), Electronics (5,07%), Construction (2,76%), Energy (2,30%), Retailing (2,30%), others (23,05%). The sample is also compounded by 10% of companies with till 100 employees, 21% from 101 to 500 employees, 13% from 501 to 1000 employees and 56% with more than 1000 employees.

Before testing the relationship between independent variables and dependent ones, we proceeded with preliminary data analysis (Forza, 2002) by the dimensions refining, which is depicted in Table 1. We verified that some dimensions have the Cronbach Alpha lower than 0,70, however, the Composite of Reliability is higher than it. It is because the Cronbach Alpha coefficient takes account of the sample size and number of items in a dimension. Thus, as the higher the number of items and sample size, the higher the reliability coefficient. In another way, the Composite Reliability was higher than 0,70 in all items, once it is calculated through the correlation among items instead of the number of questions in the dimensions (Table 1).

We subsequently estimated the factorial score of each dimension, that became independent variables, except the dimension "Outcomes" that is the dependent one. The regression analysis is depicted in Table 2.

According to Table 2, Knowledge and Strategy Alignment has a positive and significant influence on Procurement Outcomes (0,426). This influence suggests that the level of knowledge of Procurement staff upon programming, the comprehension of technological trends, strategic organizational plans, business environment, mission, vision, and firm strategy may improve the quality, compliance, and responsiveness of big data implementation in procurement. It also suggests that when a firm has objectives that are quantified, a detailed action plan and prioritize investments on Big Data analysis, the Procurement Outcomes may be enhanced as well.

The dimension Planning e Control has also a positive and significative influence on Procurement Outcomes (0,381). In this dimension, it was assessed to what extent the organization examines the innovative opportunities to use the Big Data strategically and accomplish a plan to analyze the Big Data in a systematic way. The more activities are performed to plan and control the Big Dada, the higher the results from the Procurement department.

On another hand, Coordination has a negative and significative influence on Big data Procurement Outcomes. Although participating in meetings to discuss the procurement issues may generate better results, the frequency of the meeting may hamper the performance. It was perceived in the regression analysis due to the negative and significant relationship between Coordination and Procurement Outcomes (-0,159). Therefore, we suggest that the amount of information got from multifunctional areas in so many meetings may delay the decision making and, in consequence, harm the Procurement performance. In fact, these results offer significant pieces of evidence to confirm the first hypothesis, supporting the idea that management alignment, knowledge and coordination of big data strategies impact its deployment on the procurement environment.

Considering the impact of procurement professionals' behavior, the second stage of our study intends to verify if procurers behavior impact on the deployment of big data analytics strategies on the procurement environment. We split this hypothesis into 4 hypotheses exploiting procurers' intentions and 5 hypotheses exploiting procurers' common reactions and their impact on big data deployment within the procurement environment.

We start verifying procurer's intention (price seeking, quality seeking, value-added seeking and willingness to use new technologies). We noticed that the best price seeking seems to be relevant for advancing the procurement of big data strategies. The results present a positive influence on the decision-making process, more precisely, our findings suggest that it influences procurement in 12,2%. It reinforces the idea from previous research that most initiatives to implement complex data analysis in Procurement is motivated by elementary sourcing drivers such as cost reduction. Additionally, we verified that the data accessibility and the comprehension of it to make better decisions (willingness to use new technologies) influence positively Procurement Outcomes (0,143) and is also in the line of IT literature (Davis et al., 1989; Schoenherr & Speier-Pero, 2015).

Surprisingly, Quality seeking and efforts dedicated to getting the best products in terms of quality have no influence on the use of big data in the procurement environment. Probably because quality has become a basic issue in procurement that the search for quality is a matter of qualifier criteria to buy rather than result or performance. There is no evidence that recognizing quality as related to price and choosing cheaper products rather than expensive ones' influence on Procurement outcomes. It suggests that buying products duet to its price is not a matter of performance, but a choice.

In fact, we were outraged to not find enough pieces of evidence on the relationship between the search for value-adding and the usage of big data (0,054). It demonstrates the long journey that procurement executives have to exploit to understand the relevance of using complex data in Procurement. Apparently, interest is triggered by the mere possibility of reducing

Table 1. Refining of Dimensions and Reliability Coefficients

	Dimension	Items	Factorial Score	Cronbach Alpha	Composite reliability	AVE
Organizational alignment	Knowledge and Strategy Alignment	KNA1 KNA2 KNA3 KNA4 KNA5 KNA6 KNA7 KNA8	0,815 0,814 0,841 0,851 0,795 0,816 0,811 0,779	0,928	0,94	0,67
	Planning & Control	PLC1 PLC2 PLC3 PLC4 PLC5 PLC6	0,797 0,852 0,844 0,849 0,737 0,802	0,898	0,92	0,66
	Coordination	COOl C002 C003 C004	0,853 0,809 0,809 0,781	0,829	0,89	0,66
Individual intentions	Price seeking	PSK1 PSK2	0,854 0,854	0,614	0,84	0,73
	Specification and brand seeking	BRD1 BRD2	0,830 0,830	0,545	0,82	0,69
	Quality Seeking	QLS1 QLS2 QLS3	0,818 0,739 0,784	0,678	0,82	0,61
	Value proposition	VLP1 VLP2 VLP3	0,727 0,771 0,723	0,587	0,78	0,55
	Willingness to use new technologies	WNT1 WNT2	0,784 0,784	0,372	0,76	0,61
Individual reactions	Lack of autonomy	INS1 INS2	0,788 0,788	0,391	0,77	0,62
	Resistance to change supplier	RCS1 RCS2 RCS3 RCCS4 RCS5	0,773 0,757 0,709 0,728 0,725	0,785	0,85	0,54
	Confused by Over choice	OVR1 OVR2 OVR3	0,826 0,758 0,792	0,698	0,83	0,63

	Dimension	Items	Factorial Score	Cronbach Alpha	Composite reliability	AVE
Outcomes	Willingness to pay more for Quality	WPQ1WPQ2	0,845 0,845	0,698	0,83	0,71
	Perceived overall improvement of operation al performance	OUC1 OUC2 OUC3 OUC4 OUC5 OUC6 OUC7	0,911 0,936 0,952 0,938 0,936 0,937 0,942	0,976	0,98	0,88

Source: Research data

Table 2. Regression Analysis

	Unstandardized coefficient		Standardized coefficient	t	Sig.	Collinearity		R²
	B	Error st	Beta			Tolerance	VIF	
(Constant)	-0.001416	,050		,000	1,000			0,48
Knowledge and Stratatey Aligment	,426	,072	,426	5,934	,000	,488	2,050	
Planning & Control	,381	,079	,381	4,838	,000	,405	2,470	
Coordination	-,159	,076	-,159	-2,107	,036	,441	2,266	
Price Seeking	,122	,053	,122	2,282	,024	,882	1,134	
Brand Seeking	,056	,054	,056	1,033	,303	,858	1,165	
Lack of Autonomy	-,030	,052	-,030	-,575	,566	,919	1,088	
Resistance to change supplier	-,056	,062	-,056	-,900	,369	,660	1,516	
Confused by overchoice	,025	,059	,025	,427	,670	,717	1,395	
Quality seeking	-,035	,056	-,035	-,621	,535	,794	1,260	
Willingness to pay more for Quality	,062	,057	,062	1,097	,274	,785	1,275	
Value proposition	,054	,056	,054	,965	,336	,792	1,262	
Wiilingness to use new technologies	,143	,055	,143	2,625	,009	,845	1,184	

Source: Research data

costs and it is not yet possible to understand its use to capture and generate value for the organization.

Besides, our results did not offer enough evidence to affirm that procurement professionals' reactions due to daily routine pressures and current dilemmas impact the implementation of big data initiatives. In fact, the limitations that executives face because they have very rigid specifications or brand-specific targeting do not impact the decisions of whether to use complex data. It is the same when considering the autonomy of managers to make decisions. It is because managers don´t consider that getting an opinion about the procurement process from coworkers and bosses may improve the outcomes. The results also have shown that there is no evidence that buying from the favorite brand, keeping the same suppliers, and being loyal to them, enhance the Outcomes. The resistance to change suppliers even when there are better opportunities offered by others has no influence on Outcomes. Managers also declared that the over choice does not harm the outcomes. Therefore, we believe that multiple offers are not a fact that cause confusion and affect the outcomes due to the experience of managers in procurement areas.

To summarize, we realize that the dimensions that have more influence on Outcomes are related to Big Data, which means that procurement capabilities are elementary competences and not a differential, as expected. The combination of the five significant dimensions mentioned previously explain the Procurement Big Data Outcomes in 48,1%.

DISCUSSION AND CONCLUSIONS

In line with a continuous call for addressing cross-disciplinary research (Singhal & Singhal, 2002) our study combines consumer behavior, information technology, and procurement literature for better comprehend the role of organizational alignment on big data deployment on procurement activities and the impact of procurement managers behavior in the B2B environment.

Firstly, we attempt to evaluate the relationship between organizational, procurement and big data strategies alignment. We found that several factors are relevant for procurement big data succeed: the technical and business capability of personnel involved, the preparation of the organization to support the implementation and use of big data and the frequent inter-functional discussion of opportunities, plans, and responsibilities of data analysis. All these topics joined the knowledge, coordination, and planning of big data that should precede its deployment in procurement. Results suggest that without strong support and direction of C-level, big data is an agenda without the proper understanding of how to apply and the real worth for procurement. Future studies should address this gap, exploiting the levels of technology adoption, moving from pure digitalization to real big data expertise and comparing to the level of alignment between corporate strategy and procurement strategy. Applied cases and roadmaps would be quite welcome to advance the comprehension of this phenomenon.

Secondly, we attempt to evaluate the impact of human behavior on the use and implementation of complex data analytics in the procurement environment. Our assumptions comprised that individuals must be capable and motivated to execute such actions and the environment shall offer adequate situations for development and motivation. Scholars emphasize the understanding of how an individual affects the system and outcomes (Boudreau et al., 2003). Although behaviors are relevant in change management processes, the buyer's current behaviors (intentions and reactions) do not significantly impact the deployment of big data strategies in this context, except “best price seeking” and “willingness to use new technologies”. This result seems to be coherent due to the traditional nature of the procurement role. The key driver of advancing on more assertive decision-making process is to achieve superior results on cost optimization (Chick & Handfield, 2004; Hong & Kwong, 2012; Lilien, 2016), although cost of implementation big data analytics is also a concern for practitioners (Van Knippenberg et al., 2015; Barbosa et al., 2018). In addition, the study shows that the propensity to recognize the usefulness of complex data analysis as one of the significant dimensions that can contribute to the success of the implementation of big data into a procurement role. This positive behavior is a signal of technology acceptance and it is recognized as the first stage of assimilating a new technology and process change (Davis, 1989; Karahanna et al., 1999). In fact, it reflects again a natural mindset of procurers, who intends to search for a cost-benefit outcome from every change.

On the other side, the absence of significance on other common buyers´ behaviors reframes the broad idea that behaviors are relevant in change management. Individuals immersed in constraint mindset as resistance to changes, lack of autonomy, confused by overchoicing or even the positive ones as the predisposition to pay more for quality, become secondary dimensions in the process. In fact, reactions are an individual response to a social change (Bendoly et al., 2016) and as soon as the circumstances change, reactions tend to be reshaped by the new intentions. For instance, as soon as a procurement manager will comprehend how to use big data, the overchoicing confusion should be minimized and he/she will feel more secure with the new methodologies in place. On the contrary, people transform themselves from new processes and technologies.

For this to occur effectively and to succeed in the implementation of big data on procurement roles and activities, corporate and procurement strategy must be in line. Once top management is convinced and sponsor the process change, current members’ individual behavior has a non-significant impact on the context. Moreover, a major implication of our findings for strategic sourcing and the challenges to implementing a big data-driven strategy is that knowledge and strategic alignment may serve as an important driver to support managers to comprehend how to include big data strategies among procurement decision making-process and consequently advance the value proposition of procurement role.

This study has also some limitations and researchers addressed a superior effort to mitigate them. The first issue refers to the methodology chosen and the informants’ approach. Our research was designed to inquire about a single respondent. However, some authors criticized it (e.g. MacKenzie & Podsakoff, 2012; Roh et al., 2013) arguing that it should trigger common method bias and potential respondent bias. We recognize the shortcomings of this decision and we put important efforts to mitigate potential risks for the inferences and results of this study, following literature guidelines. The first action in place was the commitment stablished between researchers and informants to assure the confidentiality and anonymity of research participants (Bell & Bryman, 2007; Wiles at al., 2008). Although this strategy is the most appropriate for the informant, because it provides a certain comfort to answer the questions in a sincere way, this also made it very hard to guarantee that our database could be composed of multiple informants. We selected carefully the population and sample by focusing on procurement managers, who were knowledgeable practitioners (Montabon et., al, 2018) involved (on daily basis) in procurement challenges and they can provide first-hand high-quality information of the phenomenon under investigation (Forza, 2002; Krause et., al, 2018). Moreover, the researchers are committed to providing a summary report with the results of the research to informants. This strategy adopted during the searching and invitation of potential informants was a way of selecting people really interested in the contribution of the study to their own work and consequently avoiding distortions in the shared data (Phillips, 1981).

Secondly, we increase our efforts to obtain responses from a substantial number of firms (Montabon et., al, 2018). Since we surveyed a single respondent for all items, the potential for respondent biases reduces. This is justified by the fact that our study focused on behavior and individual decision-making process (Flynn et al., 2018). Finally, even though that single respondent can be the Achilles' heel of the present research, all constructs were previously validated, and the objectives, framework, and context are new for addressing the research question (Flynn et al., 2018).

This research provides preliminary shreds of evidence of the phenomenon and consequently, it offers the basis for more in-deep surveys, case studies, and experiments. For deeper comprehension, future studies should explore a longitudinal perspective comparing past constraints and how organization overcomes these challenges to adopt big data analytics. Additionally, we would like to see in near future studies that compare polar cases to comprehend the differences and convergences on the decision making the process for adopting big data in procurement.

REFERENCES

Anderson, J. C., Thomson, J. B. & Wynstra, F. (2000) Combining value and price to make purchase decisions in business markets. *International Journal of Research in Marketing*, 17(4), 307-329.

Agarwal, R. & Dhar, V. (2014) Big Data, Data Science, and Analytics: The Opportunity and Challenge for IS Research. *Information Systems Research*, 25(3), 443-448.

Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., and Childe, S. J. (2016) How to improve firm performance using big data analytics capability and business strategy alignment? *International Journal of Production Economics*, 182, 113-131.

Arnold, U., Karner, H. and Schnabel, M. (2005) Target-oriented use of strategic sourcing tools: a critical analysis creating process awareness for electronic reverse auctions. *Journal of Purchasing and Supply Management*, 11 (2–3), pp.116–128.

Ateş, M. A., van Raaij, E. M. & Wynstra, F. (2018) The impact of purchasing strategy-structure (mis) fit on purchasing cost and innovation performance. *Journal of Purchasing and Supply Management*, 24(1), 68-82.

Awanis, S., Schlegelmilch, B.B., Cui, C.C. (2017) Asia's materialists: Reconciling collectivism and materialism. *Journal of International Business Studies*, 48(8), 964-991.

Badenhorst, J. A. (1994) Unethical behavior in procurement: A perspective on causes and solutions. *Journal of Business Ethics*, 13(9), 739-745.

Baier, C., Hartmann, E. & Moser, R. (2008) Strategic alignment and purchasing efficacy: an exploratory analysis of their impact on financial performance. *Journal of Supply Chain Management*, 44(4), 36-52.

Bao, Y., Zhou, K. Z. & Su, C. (2003) Face consciousness and risk aversion: do they affect consumer decision-making? *Psychology and Marketing*, 20(8), 733-755.

Barbosa, M. W., Vicente, A. D. L. C., Ladeira, M. B. & Oliveira, M. P. V. D. (2018) Managing supply chain resources with Big Data Analytics: a systematic review. International Journal of Logistics *Research and Applications*, 21(3), 177-200.

Bell, E. & Bryman, A. (2007) The ethics of management research: an exploratory content analysis. British *Journal of Management*, 18(1), 63-77.

Bello-Orgaz, G., Jung, J. J. & Camacho, D. (2016) Social big data: Recent achievements and new challenges. *Information Fusion*, 28, 45-59.

Bendoly, E., Donohue, K. & Schultz, K. L. (2006) Behavior in operations management: Assessing recent findings and revisiting old assumptions. *Journal of operations management*, 24(6), 737-752.

Bendoly, E. & Schoenherr, T. (2005) ERP system and implementation-process benefits: Implications for B2B e-procurement. *International Journal of Operations and Production Management*, 25(4), 304-319.

Boudreau, J., Hopp, W., McClain, J. O. & Thomas, L. J. (2003) On the interface between operations and human resources management. *Manufacturing and Service Operations Management*, 5(3), 179-202.

Braganza, A., Brooks, L., Nepelski, D., Ali, M. & Moro, R. (2017) Resource management in big data initiatives: Processes and dynamic capabilities. *Journal of Business Research*, 70, 328-337.

Buchanan, E. A. & Hvizdak, E. E. (2009) Online survey tools: Ethical and methodological concerns of human research ethics committees. *Journal of Empirical Research on Human Research Ethics*, 4(2), 37-48.

Byrd, T. A. & Turner, D. E. (2000) Measuring the Flexibility of Information Technology Infrastructure: Exploratory Analysis of a Construct. *Journal of Management Information Systems*, 17(1), 167-208.

Caniato, F., Luzzini, D. & Ronchi, S. (2014) Purchasing performance management systems: an empirical investigation. *Production Planning and Control*, 25(7), 616-635.

Carillo, K. D. A. (2017) Let's stop trying to be "sexy"–preparing managers for the (big) data-driven business era. *Business Process Management Journal*, 23(3), 598-622.

Carr, A.S., Smeltzer, L.R., (2000) An empirical study of the relationships among purchasing skills and strategic purchasing, financial performance and supplier responsiveness. *Journal of Supply Chain Management* 36(3), 40–54.

Carr, A.S., Pearson, J.N. (2002) The impact of purchasing and supplier involvement on strategic purchasing and its impact on the firm's performance. *International Journal of Operations and Production Management*. 22 (9), 1032–1053.

Carter, J.R., Narasimhan, R. (1996) Purchasing and supply management: future directions and trends. *Journal of Supply Chain Management*, 32 (4), 2–12.

Castells, M. (2011) *The rise of the network society*. John Wiley and Sons.

Chae, B., Olson, D. & Sheu, C. (2014) The impact of supply chain analytics on operational performance: a resource-based view. *International Journal of Production Research*, 52(16), 4695-4710.

Chen, H., Chiang, R. H. & Storey, V. C. (2012) Business intelligence and analytics: from big data to big impact. *MIS quarterly*, 1165-1188.

Chick, G. & Handfield, R. (2014) *The Procurement Value Proposition: The Rise of Supply Management*. Kogan Page Publishers.

Choo, C. W. (1996) The knowing organization: How organizations use the information to construct meaning, create knowledge and make decisions. *International Journal of Information Management*, 16(5), 329-340.

Constantiou, I. D. & Kallinikos, J. (2015) New games, new rules: big data and the changing context of strategy. *Journal of Information Technology*, 30(1), 44-57.

Cousins, P. D., Handfield, R. B., Lawson, B. & Petersen, K. J. (2006) Creating supply chain relational capital: the impact of formal and informal socialization processes. *Journal of operations management*, 24(6), 851-863.

Cox, A., Chicksand, D., Ireland, P. & Davies, T. (2005) Sourcing indirect spend: a survey of current internal and external strategies for non-revenue-generating goods and services. *Journal of Supply Chain Management*, 41(2), 39-51.

Cuganesan, S. & Lee, R. (2006) Intra-organisational influences in procurement networks control The impacts of information technology. *Management Accounting Research*, 17(2), 141-170.

Davis, F. D. (1989) Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, . DOI:10.2307/249008.

Eisenhardt, K. M. (1989) Making Fast Strategic Decisions in High-Velocity Environments. *The Academy of Management Journal*, 32 (3), 543-57.

Ellram, L. M. & Carr, A. (1994) Strategic purchasing: a history and review of the literature. *International journal of purchasing and materials management*, 30(1), 9-19.

Ernst, H. & Teichert, T. (1998) The RandD/marketing interface and single informant bias in new product development research: An illustration of a benchmarking case study. *Technovation*, 18, 721–739.

Evans, J. R. & Mathur, A. (2005) The value of online surveys. *Internet Research*, 15(2), 195-219.

Forza, C. (2002) Survey Research in operations management: a process-based perspective. International *Journal of Operations and Production Management*, 22(2), 152-194

Flynn, B., Pagell, M. & Fugate, B. (2018) Survey Research Design in Supply Chain Management: The Need for Evolution in Our Expectations. *Journal of Supply Chain Management*, 54(1), 1-15.

Gadde, L. E. & Håkansson, H. (1994) The changing role of purchasing: reconsidering three strategic issues. *European Journal of Purchasing and Supply Management*, 1(1), 27-35.

Gebauer, J. & Segev, A. (2001) Changing Shapes of Supply Chains - How the internet could lead to a more integrated procurement function. *Supply Chain Forum: An International Journal*, 2 (1), 2-9

Gerstner, E. (1985) Do higher prices signal higher quality? *Journal of marketing research*, 22(2), 209-215.

Gino, F. & Pisano, G. (2008) Toward a theory of behavioral operations. *Manufacturing and Service Operations Management*, 10(4), 676-691.

Gonzalez-Benito, J. (2007) A theory of purchasing's contribution to business performance. *Journal of Operations Management*, 25(4), 901-917.

Giunipero, L.C., Pearcy, D.H., (2000) World-class purchasing skills: an empirical investigation. *Journal of Supply Chain Management* 36 (4), 4–13.

Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B. & Akter, S. (2017) Big data and predictive analytics for supply chain and organizational performance. *Journal of Business Research*, 70, 308-317.

Hashem, I. A. T., Yaqoob, I., Anuar, N. B., Mokhtar, S., Gani, A. & Khan, S. U. (2015) The rise of "big data" on cloud computing: Review and open research issues. *Information Systems*, 47, 98-115.

Hong, P. & Kwon, H. B. (2012) Emerging issues of procurement management: a review and prospect. *International Journal of Procurement Management* 4, 5(4), 452-469.

Jacoby, J. & Kyner, D. B. (1973) Brand loyalty vs. repeat purchasing behavior. *Journal of Marketing research*, 10(1), 1-9. DOI: 10.2307/3149402

Johnston, W. J. & Lewin, J. E. (1996) Organizational buying behavior: Toward an integrative framework. *Journal of Business Research*, 35(1), 1-15.

Kache, F. & Seuring, S. (2017) Challenges and opportunities of digital information at the intersection of Big Data Analytics and supply chain management. *International Journal of Operations and Production Management*, 37(1), 10-36.

Karjalainen, K., Kemppainen, K. & Van Raaij, E. M. (2009) Non-compliant work behavior in purchasing: An exploration of reasons behind maverick buying. *Journal of business ethics*, 85(2), 245.

Kayser, V., Nehrke, B. & Zubovic, D. (2018) Data Science as an Innovation Challenge: From Big Data to Value Proposition. *Technology Innovation Management Review*, 8(3). DOI: 10.22215/timreview/1143

Kim, G., Shin, B. & Kwon, O. (2012) Investigating the value of sociomaterialism in conceptualizing the IT capability of a firm. *Journal of Management Information Systems*, 29(3), 327-362.

Kiron, D. & Shockley, R. (2011) Creating business value with analytics. *MIT Sloan Management Review*, 53(1), 57. In: https://sloanreview.mit.edu/article/creating-business-value-with-analytics/

Knudsen, D. (2003) Aligning corporate strategy, procurement strategy, and e-procurement tools. *International Journal of Physical Distribution and Logistics Management*, 33(8), 720-734.

Krause, D., Luzzini, D. & Lawson, B. (2018) Building the case for a single informant in supply chain management survey research. *Journal of Supply Chain Management*, 54, 42–50.

Kulp, S. L., Randall, T., Brandyberry, G. & Potts, K. (2006) Using organizational control mechanisms to enhance procurement efficiency: how GlaxoSmithKline improved the effectiveness of e-procurement. *Interfaces*, 36(3), 209-219.

Lilien, G. L. (2016) The B2B knowledge gap. International Journal of Research in Marketing, 33(3), 543-556.

Lonsdale, C. & Watson, G. (2005) The internal client relationship, demand management, and value for money: a conceptual model. *Journal of Purchasing and Supply Management*, 11(4), 159-171.

MacKenzie, S. B. & Podsakoff, P. M. (2012) Common method bias in marketing: Causes, mechanisms and procedural remedies. *Journal of Retailing*, 88, 542–555.

Malhotra, N. K. (1984) Reflections on the information overload paradigm in consumer decision making. *Journal* *of consumer research*, 10(4), 436-440.

Maruping, L. M., Bala, H., Venkatesh, V. & Brown, S. A. (2017) Going beyond intention: Integrating behavioral expectation into the unified theory of acceptance and use of technology. *Journal of the Association for Information Science and Technology*, 68(3), 623-637.

Mitchell, V. W., Walsh, G. & Yamin, M. (2005) Towards a conceptual model of consumer confusion. *ACR North American Advances*. Available in: http://www.acrwebsite.org/volumes/9058/volumes/v32/NA-32

Mogre, R., Lindgreen, A. & Hingley, M. (2017) Tracing the evolution of purchasing research: future trends and directions for purchasing practices. *Journal of Business and Industrial Marketing*, 32(2), 251-257.

Montabon, F., Daugherty, P. J. & Chen, H. (2018) Setting standards for single respondent survey design. *Journal of Supply Chain Management*, 54(1), 35-41.

Narasimhan, R. and Carter, J.R. (1998) Linking business unit and material sourcing strategies. *Journal of Business Logistics*, 19(2), 155-71.

Narasimhan, R. & Das, A. (2001) The impact of purchasing integration and practices on manufacturing performance. *Journal of Operations Management*, 19(5), 593-609.

Nicoletti, B. (2013) Lean Six Sigma and digitize procurement. *International Journal of Lean Six Sigma*, 4(2), 184-203.

Nollet, J. & Beaulieu, M. (2010) L'impact des technologies de linformatioi sur les structures de gestion des achats: des leçons pour la gestion de la chaîne logistique. *Logistique and Management*, 18(1), 3-16.

Paulraj, A., Chen, I.J., Flynn, J. (2006) Levels of strategic purchasing: impact on supply integration and performance. *Journal of Purchasing and Supply Management* 12 (3), 107–122.

Phillips, L. W. (1981) Assessing measurement error in key informant reports: A methodological note on organizational analysis in marketing. *Journal of Marketing Research*, 395-415. DOI: 10.2307/3151333

Pohl, M. & Förstl, K. (2011) Achieving purchasing competence through purchasing performance measurement system design—A multiple-case study analysis. *Journal of Purchasing and Supply Management*, 17(4), 231-245.

Presutti Jr, W. D. (2003) Supply management and e-procurement: creating value-added in the supply chain. *Industrial marketing management*, 32(3), 219-226.

Provost, F. & Fawcett, T. (2013) Data science and its relationship to big data and data-driven decision making. *Big data*, 1(1), 51-59.

Ramamoorti, S. & Curtis, S. (2003) Procurement fraud and data analytics. *The Journal of Government Financial Management*, 52(4), 16.

Rodríguez-Escobar, J.A., González-Benito, J. (2017) The effect of strategic alignment on purchasing management, *Management Research Review*, 40 (11), 1175-1200

Roh, J. A., Whipple, J. M. & Boyer, K. K. (2013) The effect of single rater bias in multi-stakeholder research: A methodological evaluation of buyer-supplier relationships. *Production and Operations Management*, 22, 711–725

Roßmann, B., Canzaniello, A., von der Gracht, H. & Hartmann, E. (2018) The future and social impact of Big Data Analytics in Supply Chain Management: Results from a Delphi study. *Technological Forecasting and Social Change*, 130, 135-149.

Sanders, N. R. (2014) *Big data-driven supply chain management: A framework for implementing analytics and turning information into intelligence*. NY, Pearson Education.

Setia, P. & Patel, P. C. (2013) How information systems help create OM capabilities: Consequents and antecedents of operational absorptive capacity. *Journal of Operations Management*, 31(6), 409-431.

Schoemaker, P. J. & Tetlock, P. E. (2017) Building a More Intelligent Enterprise. *MIT Sloan Management Review*, 58(3), 28.

Schoenherr, T. & Speier-Pero, C. (2015) Data science, predictive analytics, and big data in supply chain management: Current state and future potential. *Journal of Business Logistics*, 36(1), 120-132.

Singhal, K. & Singhal, J. (2012) Opportunities for developing the science of operations and supply-chain management. *Journal of Operations Management*, 30(3), 245-252.

Sheth, J. N. (1973) A model of industrial buyer behavior. *The Journal of marketing*, 50-56. DOI: 10.2307/1250358

Tassabehji, R. & Moorhouse, A. (2008) The changing role of the procurement: Developing professional effectiveness. *Journal of Purchasing and Supply Management*, 14(1), 55-68.

Terpend, R., Krause, D.R., Dooley, K.J. (2011) Managing buyer-supplier relationships: empirical patterns of strategy formulation in industrial purchasing. *Journal of Supply Chain Management*, 47 (1), 73–94.

Tippins, M. J. & Sohi, R. S. (2003) IT competency and firm performance: is organizational learning a missing link? *Strategic management journal*, 24(8), 745-761.

Van Knippenberg, D., Van Prooijen, J. W. & Sleebos, E. (2015).Beyond social exchange: Collectivism's moderating role in the relationship between perceived organizational support and organizational citizenship behavior. *European Journal of Work and Organizational Psychology*, 24(1), 152-160.

Venkatesh, V., Maruping, L.M. & Brown, S.A. (2006) Role of time in self-prediction of behavior. *Organizational Behavior and Human Decision Processes*, 100, 160–176.

Walsh, G. & Mitchell, V. W. (2010) The effect of consumer confusion proneness on word of mouth, trust, and customer satisfaction. *European Journal of Marketing*, 44(6), 838-859.

Waller, M. A. & Fawcett, S. E. (2013) Data science, predictive analytics, and big data: a revolution that will transform supply chain design and management. *Journal of Business Logistics*, 34(2), 77-84.

Walsh, G., Hennig-Thurau, T. and Mitchell, V.-W. (2007) Consumer confusion proneness: scale development, validation, and application. *Journal of Marketing Management*, 23 (7/8), pp. 697-721.

Wang, G., Gunasekaran, A., Ngai, E. W. & Papadopoulos, T. (2016) Big data analytics in logistics and supply chain management: Certain investigations for research and applications. *International Journal of Production Economics*, 176, 98-110.

Watts, C. A., Kim, K. Y. & Hahn, C. K. (1995) Linking purchasing to corporate competitive strategy. *Journal of Supply Chain Management*, 31(1), 2-8.

Westerski, A., Kanagasabai, R., Wong, J. & Chang, H. (2015) Prediction of enterprise purchases using Markov models in procurement analytics applications. *Procedia Computer Science*, 60, 1357-1366.

Weele, A. J. & Raaij, E. M. (2014) The future of purchasing and supply management research: About relevance and rigor. *Journal of Supply Chain Management*, 50(1), 56-72.

Wiles, R., Crow, G., Heath, S. & Charles, V. (2008) The management of confidentiality and anonymity in social research. *International Journal of Social Research Methodology*, 11(5), 417-428.

Zeithaml, V. A. (1988) Consumer perceptions of price, quality, and value: a means-end model and synthesis of evidence. *The Journal of marketing*, 2-22. DOI: 10.2307/1251446

Zheng, J., Knight, L., Harland, C., Humby, S. & James, K. (2007) An analysis of research into the future of purchasing and supply management. *Journal of Purchasing and Supply Management*, 13(1), 69-83.

APPENDIX

Knowledge and strategic alignment	
KNA1	Our analytics personnel are very capable in terms of programming skills
KNA2	Our analytics personnel show superior understanding of technological trends
KNA3	Our analytics personnel comprehend our organizational policies and plans at a very high level
KNA4	Our analytics personnel are very knowledgeable about the business environment
KNA5	The big data analytics plan aligns with the company's mission, goals, and strategy
KNA6	The big data analytics plan contains quantified goals and objectives
KNA7	The big data analytics plan contains detailed action plans/strategies that support company direction
KNA8	We prioritize major big data analytics investments by the expected impact on business performance
Planning and control	
PLC1	In this organization, we have structured and real-time data for making decisions
PLC2	We continuously examine the innovative opportunities for the strategic use of big data analytics
PLC3	We enforce adequate plans for the introduction and utilization of big data analytics
PLC4	We perform big data analytics planning process in systematic and formalized ways
PLC5	In our organization, the responsibility for big data analytics development is clear
PLC6	Comparing to rivals within our industry, our organization has the foremost available analytics system
Coordination	
COO1	In our organization, business analysts and line people meet frequently to discuss important issues both formally and informally
COO2	In our organization business analysts and line people from various departments frequently attend cross-functional meetings
COO3	In our organization, information is widely shared between business analysts and line people so that those who make decisions or perform jobs have access to all available know-how
COO4	In our organization, performance criteria are clear
Price seeking	
PSK1	I compare prices to find the lower-priced products
PSK2	Before making a purchasing decision I look around for the best price
Specification and brand seeking	
BRD1	Before making a purchasing decision I consider the associated reliability of the brand
BRD2	Before making a purchasing decision, I considered the reputation of the brand
Quality seeking	
QLS1	Getting very good quality is very important to me
QLS2	In general, I usually try to buy the very best overall quality products
QLS3	I make a special effort to choose the very best quality products
Value proposition	
VLP1	When it comes to purchasing products, I try to get the very best or perfect choice
VLP2	I look carefully to find the best value for the money

Knowledge and strategic alignment	
VLP3	Before making a purchasing decision, I paid attention to sales information
Willingness to use new technologies	
WNT1	In this organization, we have a lot of data but are not easily accessible for Purchases (R)
WNT2	I believe that by using big data I can take better decisions
Insecurity in decision making	
INS1	Before making a purchasing decision I ask my colleagues opinion
INS2	Before making a purchasing decision, I ask my boss opinion
Resistance to change suppliers	
RCS1	Once I find a product or brand I like, I stick with it
RCS2	I have favorite brands I buy over and over
RCS3	I go to the same suppliers each time I procure
RCS4	I am loyal to certain stores and brands
RCS5	I would rather stick with a brand I usually buy than try something I am not very sure of
Confused by overchoice	
OVR1	There are so many brands to choose from that I often feel confused
OVR2	Sometimes it's hard to choose which suppliers to buy
OVR3	All the information I get on different products confuses me.
Willingness to pay more for quality	
WPQ1	The more expensive brands are usually my choices.
WPQ2	The higher the price of a product, the better it's quality
Perceived overall improvement of operational performance	
OUC1	Considering the last 3 years, using big data analytics improved the overall quality of suppliers
OUC2	Considering the last 3 years, using big data analytics improved delivery accuracy of suppliers
OUC3	Considering the last 3 years, using big data analytics impacted on overall costs reduction
OUC4	Considering the last 3 years, using big data analytics reduced overall risks from suppliers
OUC5	Considering the last 3 years, using big data analytics improved the responsiveness of suppliers
OUC6	Considering the last 3 years, using big data analytics improved forecast of suppliers
OUC7	Considering the last 3 years, using big data analytics improved compliance of our process

ENDNOTES ARTICLE

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