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MARCELO WERNECK BARBOSA

INTER-ORGANIZATIONAL COLLABORATION AND ORGANIZATIONAL PERFORMANCE: THE MEDIATING EFFECT OF BIG DATA ANALYTICS CAPABILITIES AND THE MODERATING EFFECT OF TECHNOLOGICAL DYNAMISM AND COMPETITIVE INTENSITY

Belo Horizonte
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Orientador: Prof. Marcelo Bronzo Ladeira
Co-orientador: Prof. Alberto de la Calle Vicente

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ATA DA DEFESA DE TESE DE DOUTORADO EM ADMINISTRAÇÃO do Senhor **MARCELO WERNECK BARBOSA,** REGISTRO Nº 223/2019. No dia 28 de fevereiro de 2019, às 14:00 horas, reuniu-se na Faculdade de Ciências Econômicas da Universidade Federal de Minas Gerais - UFMG, a Comissão Examinadora de Tese, indicada pelo Colegiado do Centro de Pós-Graduação e Pesquisas em Administração do CEPEAD, em 18 de fevereiro de 2019, para julgar o trabalho final intitulado **"INTER-ORGANIZATIONAL COLLABORATION AND ORGANIZATIONAL PERFORMANCE: THE MEDIATING EFFECT OF BIG DATA ANALYTICS CAPABILITIES AND THE MODERATING EFFECT OF TECHNOLOGICAL DYNAMISM AND COMPETITIVE INTENSITY"**, requisito para a obtenção do **Grau de Doutor em Administração**, linha de pesquisa: **Mercadologia, Administração Estratégica e Operações.** Abrindo a sessão, o Senhor Presidente da Comissão, Prof. Dr. Marcelo Bronzo Ladeira, após dar conhecimento aos presentes o teor das Normas Regulamentares do Trabalho Final, passou a palavra ao candidato para apresentação de seu trabalho. Seguiu-se a arguição pelos examinadores com a respectiva defesa do candidato. Logo após, a Comissão se reuniu sem a presença do candidato e do público, para julgamento e expedição do seguinte resultado final:

(X) APROVAÇÃO;

( ) APROVAÇÃO CONDICIONADA A SATISFAÇÃO DAS EXIGÊNCIAS CONSTANTES NO VERSO DESTA FOLHA, NO PRAZO FIXADO PELA BANCA EXAMINADORA (NÃO SUPERIOR A 90 NOVENTA DIAS);

( ) REPROVAÇÃO.

O resultado final foi comunicado publicamente ao candidato pelo Senhor Presidente da Comissão. Nada mais havendo a tratar, o Senhor Presidente encerrou a reunião e lavrou a presente ATA, que será assinada por todos os membros participantes da Comissão Examinadora. Belo Horizonte, 28 de fevereiro de 2019.

NOMES	ASSINATURAS
Prof. Dr. Marcelo Bronzo Ladeira ORIENTADOR (CEPEAD/UFMG)	Marcelo Bronzo Ladeira
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ABSTRACT

Companies need to implement strategies for collaboration with supply chain partners to make more efficient use of limited resources, manage suppliers' knowledge, integrate and coordinate production and information flows through the whole supply chain. Collaboration helps organizations gain competitive advantages and improve performance in different ways, such as in terms of financial gains, productivity improvement, reduction of inventory levels and order fulfillment process improvement. It has been possible due to the integration of widespread business information systems, which tend to produce large volumes of information that are beyond the company boundaries to be analyzed. The analysis of such large volumes of data is called in general terms Big Data Analytics (BDA). In order to fully extract benefits from BDA, organizations need to develop analytical capabilities, which may involve managerial, technical and human capabilities, among others. One of the industries that have the potential of extracting most benefits from the adoption of BDA is the retail industry. Retailers are continuously innovating in order to overcome the competition and take advantage of advancing technology. The objective of this research is to understand how collaboration among companies, especially when supported by BDA capabilities, contributes to increasing organizational performance. Besides, we were also interested in analyzing how the dynamic and competitive environment in which retail organizations moderate the impact BDA capabilities might have on organizational performance. In a quantitative study conducted with 323 medium and large-sized Brazilian retail companies, we have found out that inter-organizational collaboration has a direct effect on organizational performance as well as that BDA capabilities mediate such relationship. No moderating effect of technological dynamism and competitive intensity was observed. For scholars, this research explores the relationship between collaboration, analytics and organizational performance. Prior research has largely focused on the adoption of analytics in just one company alone, ignoring the influences collaboration might have on such relationships. Besides, the research specifically examined the mediating role of BDA capabilities in modelling the relationship between inter-organizational collaboration and organizational performance as well as the moderating effect that technological dynamism and competitive intensity may have in such relationship. For practitioners, this study identifies the capabilities that contribute the most to organizational performance when establishing collaboration relationships with supply chain partners. Finally, we expect to stimulate companies to develop collaboration relationships with partners in order to achieve better performance.

Keywords: supply chain collaboration, BDA capabilities, technological dynamism, competitive intensity, organizational performance, relational view theory, SEM.

FIGURES

TABLES

ACRONYMS

AVE – Average Variance Extracted

BDA - Big Data Analytics

BA - Business Analytics

BI - Business Intelligence

BI&A - Business Intelligence and Analytics

CEO – Chief Executive Officer

CMV - Common Method Variance

CPR - Continuous Replenishment Planning

CPFR – Collaborative Planning, Forecasting and Replenishment

CPV - Customer Perception of Value

CRM - Customer Relationship Management

CSV - Customer Service Management

DeM - Demand Management

ECR - Efficient Consumer Response

EDI - Electronic Data Interchange

ETL - Extract, Transform and Load

GSCF - Global Supply Chain Forum

GoF - Goodness-of-Fit

GPS – Global Positioning System

IBGE - *Instituto Brasileiro de Geografia e Estatística*

IS - Information Systems

IT - Information Technology

JIT - Just-in-time

MFM - Manufacturing Flow Management

OLAP - Online Analytical Processing

OrF - Order Fulfillment

PLS - Partial Least Squares

PLS-SEM - Partial Least Squares – Structural Equation Modelling

PDC - Product Development and Commercialization

RFID - Radio Frequency Identification Device

RBV - Resource-based View

ROI - Return On Investment

RV – Relational View

ReM - Returns Management

SEM – Structural Equation Modeling

SKU – Stock-Keeping Unit

SRM - Supplier Relationship Management

SCA - Supply Chain Analytics

SCM - Supply Chain Management

SCOR - Supply Chain Operations Reference

VAF - Variance Accounted For

VMI - Vendor Managed Inventory

VRIN - Valuable, Rare, Imperfectibly Imitable and Non-Substitutable

INDEX

1. Introduction

One of the main concerns of the Supply Chain Management (SCM) is to coordinate the independent players in the pursuit of common goals in changing market conditions. In order to do so, companies implement strategies for collaboration with supply chain partners to make more efficient use of limited resources, manage suppliers' knowledge, integrate and coordinate production and information flows through the whole supply chain (MONTOYA-TORRES; ORTIZ-VARGAS, 2014). This strategy may be successful because nowadays companies focus on maximizing profits across the supply chain rather than maximizing their own profit and prefer having a more integrated supply chain rather than a fragmented chain (AFSHAN; CHATTERJEE; CHHETRI, 2018). The coordination of these supply chain members is called supply chain collaboration, or in this text, just collaboration. The fundamental rationale behind it is that a single company cannot successfully compete by itself (MIN et al., 2005).

Cai et al. (2016) define supply chain collaboration as "a mechanism that combines and deploys external and internal resources across a supply chain to help firms achieve goals that cannot be easily attained alone". Collaboration with supply chain partners is based on trust, good will, information exchange, social norms and a high degree of management involvement between the buyer and the supplier rather than impersonal and legal contracts, firm rules, and fixed goals (NARAYANAN; NARASIMHAN; SCHOENHERR, 2015; ZHANG; CAO, 2018). Supply chain collaboration can produce significant benefits to its partners, by reducing or sharing risks, accessing complementary resources, and decreasing costs (ZHANG; CAO, 2018). Besides, collaborating with more experienced partners provides a firm with mechanisms for learning managerial and organizational skills needed to launch competitive actions with speed and efficiency. The reason a firm engages in collaborative relationships is to actively seek to develop new and improved processes, practices, and strategies, to capitalize on partner skill and expertise, or even fulfill a business necessity (RALSTON; RICHEY; GRAWE, 2017).

Many existing studies have focused on studying the performance implications of supply chain collaborations (AFSHAN; CHATTERJEE; CHHETRI, 2018; CAO; ZHANG, 2011; MIN et al., 2005; NARAYANAN; NARASIMHAN; SCHOENHERR, 2015; SINGH et al., 2009). There is empirical evidence that demonstrates that collaboration helps organizations gain competitive advantages and improve performance in different ways, such as in terms of financial gains, productivity improvement, inventory levels reduction, order fulfillment process improvement and even errors reduction (CAI et al., 2016). Afshan et al. (2018), for instance, found out that collaboration has a positive impact on firms' financial performance, increasing their return on investment and return on sales. Firms invest time and money in establishing collaborations with the objective of maximizing profitability across the supply chain.

Collaboration between firms can produce different positive outcomes besides increasing financial results. Ralston et al. (2017) claimed that it may have positive influence on new product development processes and relationships with customers, which could eventually increase customer satisfaction. Montoya-Torres and Ortiz-Vargas (2014), in a literature review of studies published on the subject, found out that, through information sharing, one of the main components of collaboration, companies improve their inventory levels, planning processes and orders. The authors also observed that information sharing is mainly studied at the operational level, for solving problems related to the order fulfillment process such as product delivery or order replenishment. Finally, Narayanan et al. (2015) corroborate these findings but highlight that the performance improvements of collaboration are non-linear, which means that organizations need to establish a certain level of collaboration before its positive impact can be realized.

However, supply chain collaboration alone may be insufficient because firms need to use particular techniques and technologies to leverage the learning effects and improvements from the collaboration with their partners. In this sense, information technology (IT)-related capabilities may facilitate the learning effects, information and resource sharing from supply chain collaboration (CAI et al., 2016). Moreover, nowadays, organizations depend on different types of resources such as technology resources, technical and managerial skills and IT business systems. Being able to efficiently manage these resources is a distinguishable ability not only for organizations, but also for supply chains because competing in today's business environment precipitates the need for successful integration and collaboration among supply chain partners (STEFANOVIC; STEFANOVIC, 2009).

Despite major investments in information systems (IS), businesses are still struggling to achieve competitive advantage, which may be gained by the efficient management of specific resources that are valuable, rare, imperfectibly imitable and non-substitutable (VRIN) (BARNEY, 1991). Hence organizations need to support the analysis and application of information captured from such systems in order to pursue this advantage (RANJAN, 2009; SANGARI; RAZMI, 2015).

Vera-Baquero et al. (2015) argue that the latest advances in technology made it possible for organizations to cooperate due to the integration of widespread business information systems in large and complex supply-chain scenarios. These systems tend to produce large volumes of information that are beyond the company boundaries to be analyzed. This has experienced an incredible growth of event data in corporations that need to be merged for analysis. Ilie-Zudor et al. (2015) state that logistics networks generate around 1.6 billion new data items every month. The analysis of such large volumes of data is called in general terms Big Data Analytics (BDA).

In order to extract benefits from BDA, organizations need to develop analytical capabilities. As such capabilities become more sophisticated and the amount of data available increases, the opportunities for generating value and competitive advantage from them grows (GILLON et al., 2012). Previous research has identified benefits for organizations that are able to develop analytical capabilities (CHAE; OLSON, 2013; SANGARI; RAZMI, 2015; TAYLOR, 2015), such as the ones related to infrastructure or personnel expertise. Still, there is little knowledge about how organizations build these capabilities (GUPTA; GEORGE, 2016) and it is known that investing in analytical capabilities is costly (PARK; BELLAMY; BASOLE, 2016).

Big data require new forms of inter-organizational integration to uncover large hidden values from large data sets that are diverse, complex and of a massive scale (JI-FAN REN et al., 2017). In this sense, organizations that do not have control over specific and strategic resources are forced to partner with other companies, or an existing network, that does control such resources in order to survive (HAZEN et al., 2016). However, only few firms have truly capitalized on the potential of supply chain collaboration. Therefore, the value creation of collaboration should be investigated further to determine how its potential benefits can be acquired and its drawback minimized (CAI et al., 2016). Supply chains may be improved with a view on shared goals, values and experiences and an effort to improve performance (HAZEN et al., 2016), and this goal may require a large-scale intelligent infrastructure, between supply chain partners, for merging data, information, physical objects, products and business processes. Companies that take advantage of these capabilities achieve advantages over their competitors (WU et al., 2016).

In order to fully unlock the potential of BDA-enabled information availability across the supply chain, companies are required to adopt cross-functional integration and collaboration approaches with key partners. As such, the integrated supply chain approach to collaboration through data and information sharing is valued as an opportunity at the supply chain level (KACHE; SEURING, 2017). We understand that such relationship may be investigated on a supply chain context or on relationships among different dyads. Soosay and Hyland (2015) corroborate this idea stating that a supply chain comprises a network of firms, and so, collaboration should be viewed from a dyadic or multi-firm perspective. Besides, Richey et al. (2016) argue that there is a scarcity of research on Big Data as a supply chain construct and Kache and Seuring (2017) say that only few scholarly journal articles consider BDA from a SCM perspective. Moreover, Richey et al. (2016) state that researchers and practitioners are interested in investigating how Big Data can have an impact on capabilities within and across firms as they may be essential for success in the global supply chain as well as influencing other businesses capabilities and opportunities.

Sharma, Mithas and Kankanhalli (2014) state that it is still vaguely understood how BDA can create value for organizations. Besides, authors claim that the thesis that BA leads to value needs deeper analysis. Moreover, Shuradze et al. (2016) state that most studies in the literature focus on the outcomes of data analytics on different organizational issues, but few studies explore data analytics from a capabilities perspective. In such context, organizations should be most interested in developing capabilities that lead to competitive advantage. In this study, we consider BDA as an organizational capability as it represents the comprehensive capabilities that involve the interaction between IT assets and other firm resources (COSIC; SHANKS; MAYNARD, 2015).

The quest for competitive advantage has been discussed from different strategy perspectives, among which Resource-Based View (RBV) stands out (BARNEY, 1991). RBV is evolving, extending its focus from internal resources to a broader vision that incorporates the importance of relational resources and the institutional environment in which firms are embedded, to the establishment of competitive advantage (VIANA; DE SOUSA-FILHO, 2017). Among the different theories that have been extended from RBV, the Relational View (RV) is the background theory of this research.

The core premise of RV suggests that firms' critical resources are embedded in interfirm interactions and routines (DYER; SINGH, 1998). For this reason, the relationships in which firms are embedded may influence their performance. According to RV, relation-specific assets, knowledge-sharing routines, complementary resources and capabilities, and effective governance constitute critical sources of inter-organizational advantage (DYER; SINGH, 1998). These four factors can be viewed as essential relational resources that should be developed and maintained by firms in order to compete successfully across markets (GOLGECI et al., 2018).

One of the industries that have the potential of extracting most benefits from the adoption of BDA is the retail industry, whose structure connects manufacturers to consumers by providing products and services from the producer to the consumer and is one of the largest and most diversified operations in the world, according to Kumar et al. (2017). Few industries have greater access to data around consumers, products, and channels than the retail industry. Consequently, retailing organizations have adopted big data and its technologies earlier than many other industries (GUTIERREZ, 2015). In retailing, data are typically large in volume, in variety (unstructured data on sales of different formats, inventory data, customer social media data), and in velocity (the speed with which data is created and updated) (BRADLOW et al., 2017). Although retail strategies may focus on different levels (market, firm, store and customer) according to Kumar et al. (2017), most BDA initiatives seem to be concentrated on the customer level. Brock and Khan (2017) identified that most of their survey respondents use or intend to use BDA for customer intelligence. According to the Centre of Economics and Business Research, customer intelligence is the area in which BDA can deliver the most economic benefit among areas of BDA application (CEBR, 2012).

For the retail industry, a purchase provides a multitude of disparate information, including transactional data (e.g., price paid, quantity purchased, shopping basket composition), consumer data (e.g., gender, age, family composition), and environmental data (e.g., technological disruptions, tax/regulations policies, consumer culture, political and economic environment). Retailers that can draw effective insights from big data and can make better predictions about consumer behavior, design more appealing offers, better target their customers, and develop tools that encourage consumers to make purchase decisions that favor their products (GREWAL; ROGGEVEEN; NORDFÄLT, 2017). In this way, the retail industry can exploit real-time information about customer preferences in order to offer customized product recommendations and pricing (ALOYSIUS; HOEHLE; VENKATESH, 2016).

The retail industry is finding it increasingly difficult to gain competitive advantage since markets are saturated and it is hard to differentiate product and price. As so, retailers need to broaden their efforts to develop strategies that result in positive impacts on customer satisfaction (COTTET; LICHTLÉ; PLICHON, 2006). However, fully exploiting the whole potential of BDA is one of the keys to retailers' success since customer relationships are the underlying resource for building customer value, which is the key to increasing enterprise value (ANDERSON; JOLLY; FAIRHURST, 2007). Moreover, the future of big data and the retail industry is very promising (GUTIERREZ, 2015) since retailers can increase their operating margins by 60% through tapping into hidden values in big data (ZHAN et al., 2016). Finally, previous research suggest that, among different industries, retailers seem to benefit the most from increases in deployment of analytics (GERMANN et al., 2014). Besides, researchers have claimed for more studies involving different sectors other than the manufacturing industry (BARBOSA et al., 2017).

Retailers are continuously innovating in order to attract more consumers, overcome the competition, and take advantage of advancing technology (MIOTTO; PARENTE, 2015). The speed in which technology changes in a specific market is called technological dynamism (JAWORKSI; KOHLI, 1993). The retailing sector is usually characterized as being highly competitive and dynamic in terms of technological advances and innovation, especially in Brazil (GHISI et al., 2008).

As BDA is acknowledged as a competitive necessity both for the supply chain and companies individually, future research of its impact upon all firm performance outcomes is highly valuable (HAZEN et al., 2016). Despite the strong appeal of the concept, empirical evidence about how BDA capabilities contribute to superior firm performance is lacking (AKTER et al., 2016). No empirical research exists assessing how BDA can bring business value. Besides that, most BDA academic studies focus on analyzing business value from a data or system perspective and the remaining literature addresses the manufacturing industry primarily (CÔRTE-REAL; OLIVEIRA; RUIVO, 2017). Therefore, studies on BDA contributions on specific sectors are needed.

1.1 Objectives

In view of the points presented previously, the objective of this research was to understand how collaboration among companies, especially when mediated by BDA capabilities, contributes to increasing organizational performance (financial performance, order fulfillment performance and perception of value). Besides, we were also interested in analyzing whether the dynamic and competitive environment in which retail organizations are operating moderates the relationship between BDA capabilities and organizational performance.

In order to achieve the general objective, the following specific objectives are presented:

- Assess the influence inter-organizational collaboration has on perception of value;
- Assess the influence inter-organizational collaboration has on order fulfillment performance;
- Assess the influence inter-organizational collaboration has on financial performance;
- Assess whether BDA Capabilities mediate the relationship between inter-organizational collaboration and organizational performance;
- Assess whether technological dynamism and competitive intensity moderate the relationship between inter-organizational collaboration and organizational performance.

Considering the objectives presented, this thesis answers the following research questions:

- RQ1: Does inter-organizational collaboration influence organizational performance?
- RQ2: Do BDA capabilities mediate the relationship between inter-organizational collaboration and organizational performance?
- RQ3: Do technological dynamism and competitive intensity moderate the relationship between BDA capabilities and organizational performance?

In order to achieve these objectives, a survey questionnaire was distributed to key informants who work with Supply Relationship Management, Information Technology, Purchasing and Marketing, in Brazilian retail and wholesale organizations. The focus of the research was in medium and large companies, since BDA initiatives are more expected to be implemented in such companies. The data obtained was analyzed using Partial-least squares method (PLS). The evaluation of the measurement model comprises unidimensionality analysis, convergent validity analysis and discriminant validity analysis. After running the PLS algorithm, estimates were obtained for the structural model relationships, which represent the hypothesized relationships among the constructs.

1.2 Contributions

This thesis aims to have contributions to both researchers and practitioners. In a BDA and SCM research context, this research extends the literature in big data exploring the relationship between collaboration, analytics and organizational performance. Prior research has largely focused on the adoption of analytics in just one company alone, ignoring the influences collaboration might have on such relationships. Second, the research specifically examined the mediating role of BDA capabilities in modelling the impact of inter-organizational collaboration in organizational performance. Third, this research also examined the moderating effect that technological dynamism and competitive intensity may have in the relationship between BDA capabilities and organizational performance. Besides, there are theoretical gaps regarding the contribution of SCM to competitive advantage in traditional industries, in an emerging economies context, such as Latin America. Moreover, analyzing SCM with relational view lenses can improve academic and managerial understandings about competitive advantage in supply chains (VIANA; DE SOUSA-FILHO, 2017).

For practitioners, this study demonstrates how best to use BDA capabilities to improve organizational performance, in terms of order fulfillment processes, financial performance and perception of value, answering a call for more research focused on distinguishing between value of supply chain collaboration and specific types of financial and operational performance (RALSTON; RICHEY; GRAWE, 2017). This study aims to justify investments on the development of specific BDA capabilities. Besides, practitioners might feel stimulated by the results of this research to develop collaboration relationships with partners in order to achieve better performance. Engaging in such relationships is a time-consuming and costly process, and the associated risks are numerous (MOURI; BINDROO; GANESH, 2015). Several inter-organizational collaboration initiatives fail because of lack of trust, problems in integrating processes and sharing information. While there are countless factors to consider when engaging in a relationship, this study offers insights from different perspectives that can help managers make informed decisions, therefore increasing the chances of success in those relationships. More specifically, from a managerial perspective, knowing a priori the capabilities that contribute to organizational performance when establishing collaborative relationships with a particular partner would be helpful to managers in maximizing the benefits realized from these relationships.

This thesis is organized as follows. Section 2 presents our theoretical background, which covers subjects from relationships and collaboration among companies, big data, BDA capabilities and technological dynamic and competitive intensity in contemporary markets. Section 3 describes the methodology that was used in this research and the characterization of the research strategy, units of observation and analysis as well as techniques that were used in order to collect and analyze research data. Then, Section 4 describes the results of this study while Section 5 presents the analyses of such results. Section 6 presents our conclusions, the limitations to this study and opportunities for future studies.

2. Theoretical Background

2.1 Supply Chain Management practices

Mentzer et al. (2001, p.4) define a supply chain as “a set of three or more entities (organizations or individuals) directly involved in the upstream and downstream flows of products, services, finances and/ or information from a source to a customer”. The authors categorize a supply chain in three levels: (1) direct supply chain, which includes the company, a supplier, and a customer involved in the upstream and/or downstream flows of products, services, finances, and/or information; (2) the extended supply chain, which comprises suppliers of the immediate supplier and customers of the immediate customer, and finally; (3) the ultimate supply chain including all the organizations involved in all the upstream and downstream flows of products, services, finances, and information from the ultimate supplier to the ultimate customer. To Raisinghani and Meade (2005), a supply chain consists of all stages involved, directly or indirectly, in fulfilling a customer request. The supply chain not only includes the manufacturer and suppliers, but also transporters, warehouses, retailers and customers themselves. Supply chain involves raw material and component suppliers, manufacturers, distributors and retailers until the finished products reach end customers (RAMANATHAN; GUNASEKARAN; SUBRAMANIAN, 2011).

Stock and Boyer (2009) argue that there are multiple definitions and nuances of the term Supply Chain Management in the literature. Mentzer et al. (2001) define SCM as “the systemic, strategic coordination of the traditional business functions and the tactics across these business functions within a particular company and across businesses within the supply chain, for the purposes of improving the long-term performance of the individual companies and the supply chain as a whole”. Jabbour et al. (2011) define SCM as an integrated approach beginning with planning and control of materials, logistics, services, and information stream from suppliers to manufacturers or service providers to the end client. SCM presents a holistic, organizational, and inter-organizational focus and involves multiple interrelated firm and interfirm processes. Supply chain research also involves phenomena possessing complex behavioral dimensions at both the individual and organizational levels (RANDALL; MELLO, 2012).

Over the past few decades, more executives have realized the strategic importance of SCM and recognized the distinctive competitive advantages that a well-managed supply chain can yield to companies (SHI; YU, 2013). SCM has experienced several stages of development since its inception, from the traditional procurement and supply management, to the subsequent production operation management and logistics management, and to the integration management from supplier to customer, from logistics to the capital, information and even decision-making flows (LIU, 2010). SCM has been seen as a tool for gaining competitive advantage through real-time collaboration with trading partners, and offers a way to rapidly plan, organize, manage, measure and deliver new products or services (STEFANOVIC; STEFANOVIC, 2009).

SCM is implemented through the execution of different SCM practices. Li et al. (2005) define SCM practices as the set of activities undertaken by an organization to promote effective management of its supply chain. From a literature review and consolidation, the authors identified six dimensions of SCM practices: strategic supplier partnership, customer relationship, information sharing, information quality, internal lean practices and postponement. Several definitions of SCM practices are found in the literature, ranging from approaches applied to integration, managing and coordination of supply, demand and relationships with involved organizations. In order to identify how authors define SCM practices, Jabbour et al. (2011) observed that there is not a pattern in defining and adopting indicators and constructs for SCM practices. Table 1 depicts and extends their work showing how previous research has characterized SCM practices.

In general, SCM practices involve different types of relationships (supplier relationships, customer relationships), best practices related to SCM processes (postponement, communication, delivery practice, lean practices, Just-in-time (JIT) production) and the use or dependency of technology (e-commerce, enterprise software and integration). As it can be observed from Table 1, supply chain integration, information sharing and quality, as well as supplier and customer relationship management are considered important SCM concepts and practices and are cited by more studies as such.

Although varying definitions of SCM exist, most scholars have agreed that SCM includes coordination and integration, as well as huge cooperation efforts among chain members (STOCK; BOYER, 2009). Integration among companies has been made possible mainly due to the wide adoption of Customer Relationship Management (CRM) and SCM software that has allowed enterprises to fully interface/integrate their demand and supply chains. Based on this integration, enterprises are able to capture up-to-the-minute data about the demand of a particular product (KOHAVI; ROTHLEDER, 2002).

In order to develop collaboration and integration relationships, organizations need to invest money, resources and time to make them work. Ritter et al. (2003) claim that the relationship between two dyads is the aggregate of episodes between two actors because the dyad has a history, which is remembered by the actors involved (and others). Isett and Provan (2005) state that important studies in the field have shown that firms that develop long-term, trust-based relationships with other organizations typically build these relationships on knowledge gained through previous interactions with these same organizations.

Table 1 - Supply Chain Management Practices*

Constructs / References	(KEAH CHOON, 2002)	(LI et al., 2005)	(ZHOU; BENTON, 2007)	(CHOW et al., 2008)	(ROBB; XIE; ARTHANARI, 2008)	(JABBOUR et al., 2011)
Supply chain integration	✔					✔
Information sharing	✔	✔		✔		✔
Supply chain characteristics	✔			✔		
Customer management	✔					✔
Supplier management				✔		
Geographical proximity	✔					
JIT capability / JIT production	✔		✔			
Supplier relationships		✔			✔	✔
Customer relationships		✔			✔	✔
Information quality		✔				
Internal lean practices		✔				
Postponement		✔				✔
Supply chain planning			✔			
Delivery practice			✔			
Communication and speed				✔		
E-commerce					✔	
Enterprise software					✔	

*adapted from Jabbour et al. (2011)

Several practices displayed in Table 1 involve, to some degree, the collaboration among organizations participating in the supply chain, for instance, supply chain integration, information sharing, and customer and supplier relationships management. Since it is so important to the SCM area and to this research's objectives, inter-organizational collaboration is discussed in more detail in the next section.

2.2 Inter-organizational collaboration

Supply chains are operating in more dynamic environments, characterized by globalization, rapidly evolving technologies and increased customer responsiveness, and as so, demand more integrative and collaborative efforts (SOOSAY; HYLAND, 2015). Supply chain collaboration has been identified as central to organizations in order to develop competitive advantages, according to Kumar and Banerjee (2014). In general, businesses with similar objectives work closer to achieve excellence in common supply chain processes such as planning, forecasting and replenishment (RAMANATHAN; GUNASEKARAN; SUBRAMANIAN, 2011). Horvath (2001) states that the driving force of effective SCM is collaboration, since strategic SCM requires collaboration among all echelons in the value chain, no matter what their size, function or relative positions. As so, supply chain collaboration refers to a mechanism that combines and deploys external and internal resources across a supply chain to help firms achieve goals that cannot be easily attained alone (CAI et al., 2016).

The keystone of SCM is to strengthen the competitive power by integrating the business processes, technology and management abilities of its participants. Inter-organizational collaboration, or simply collaboration, is a process in which organizations share resources, responsibilities, risks and information so as to jointly plan and execute a group of activities for shared goals that generates value jointly (VEDPAL; JAIN; BHATNAGAR, 2012).

Collaboration involves long-term relationships based on relationship building, joint development and information sharing regarding costs and capabilities with customers and suppliers, as companies consider their partners' processes as extensions of their own (NÄSLUND; HULTHEN, 2012). To Soosay and Hyland (2015), collaboration involves several firms or business entities in a relationship that aims to share improved outcomes and benefits. To achieve this goal, organizations need to establish an adequate level of trust, share critical information, make joint decisions and integrate supply chain processes, when necessary. Similarly, Cao, Vonderembse and Zhang (2010) define supply chain collaboration as "a long-term partnership process where supply chain partners with common goals work closely together to achieve mutual advantages that are greater than the firms would achieve individually".

When companies collaborate, they establish relationships, also called interfirm or inter-organizational relations, with the following characteristics: these relationships have long-term orientation, change over time (dynamic), do not come free from costs and are mainly maintained for an economic purpose (RITTER; RITTER; GEMU, 2003). Apart from tools, systems, processes and defined leaderships, collaboration demands a special culture that defines how individuals work, share and act, besides their learning attitude. A great deal of businesses is based on the information sharing and proper use of shared data (RAMANATHAN; GUNASEKARAN; SUBRAMANIAN, 2011), and that is a reason why collaboration is so important.

Soosay and Hyland (2015) found that many authors tend to use the term collaboration rather loosely, sometimes using coordination and integration as synonyms. Coordination occurs at a higher level where a continuous flow of critical and essential information takes place using information technology. Additionally, collaboration is higher than coordination, since at this stage, a high level of commitment, trust and information sharing is required. Collaboration goes beyond integration by including long-term commitments to technology sharing, closely integrated planning, and control systems. The exchange of information and resources is a basic form of collaboration. Companies collaborate to complement their resources in order to execute operations required to meet demands, and share private data among collaborative partners as a premise, necessary to make an efficient supply chain. According to Kumar and Banerjee (2014), collaboration is largely a social process while information sharing is largely a technological process. However, Näslund and Hulthen (2012) stress that no clear distinction between collaboration and coordination has been made in many articles.

Besides collaboration and coordination, integration is also a frequently studied topic in SCM research. Näslund and Hulthen (2012, p. 496) define SCM integration as "the coordination and management of the upstream and downstream product, service, financial and information flows of the core business processes between a focal company and its key supplier (and potentially the supplier's key suppliers) and its key customer (and potentially the customer's key customers)". Stevens and Johnson (2006, p. 22), in turn, define supply chain integration as "the alignment, linkage and coordination of people, processes, information, knowledge, and strategies across the supply chain among all points of contact and influence to facilitate the efficient and effective flows of materials, money, information, and knowledge in response to customer needs".

The integration of SCM systems has been the subject of significant debate and discussion. As organizations seek to develop partnerships and more effective information links with trading partners, internal processes become interlinked and span the traditional boundaries of firms. Physical logistics become more dependent on information technologies, and these technologies can become enablers of further cooperative arrangements. Firms are then faced with the management of an extended enterprise as a network of processes, relationships and technologies creating an inter-dependence and shared destiny (POWER, 2005).

Integration may involve different areas of integration: flows (physical, information, and financial), processes and activities, technologies and systems, and integration of actors (structures and organizations), according to Näslund and Hulthen (2012), who also state that there are four stages to supply chain integration. It starts at an early stage of product development and includes full management involvement at all levels. The first stage is characterized by sharing information on products, processes and specification changes. The second stage involves technology exchange and design support, while the third stage comprises a focus on strategic rather than tactical issues. In the fourth stage, the scope of integration is expanded to suppliers and customers. The focus is changed from being product-oriented to being customer-oriented. The attitude is altered away from adversarial to mutual support and cooperation.

Näslund and Hulthen (2012) state that a frequent debate is the relationship between internal and external integration. Internal integration (intra-organizational) is thought of almost as a prerequisite for SCM integration, having the elimination of traditional functional "silos" and better coordination among functional areas as goals. External integration, on the other hand, represents the integration of the activities and the flows across organizational boundaries. It is related to the coordination and collaboration with other supply chain participants. Other common definition is that forward integration refers to integration with customer while backward integration, represents integration with suppliers. Although integration could include several members of a supply chain, in reality, the dyadic integration is still the most common.

To build supply chains that collaborate well, it is essential to understand how firms share information, integrate processes, communicate and jointly create knowledge with their partners (CAO; VONDEREMBSE; ZHANG, 2010). The level of collaboration is determined by characteristics of the market, such as demand and supply uncertainty, the product (criticality and customization level) as well as the partner characteristics, like superior capabilities and dependence (SCHOLTEN; SCHILDER, 2015). However, the ability for firms to utilize shared resources is a direct function of the amount and quality of resources shared. For example, inter-organizational information systems are only as profitable as a function of the quality and quantity of information they store and share (FAWCETT; MAGNAN; MCCARTER, 2008). Horvath (2001) state that the infrastructure capacities required for each participant of a supply chain vary, but certainly include open and low-cost connectivity, very large, flexible and multimedia data storage capabilities, systems and channel integration, higher-level self service capabilities, intelligence gathering and analysis, sophisticated security capabilities and new electronic commerce capabilities.

Several benefits of collaboration have been presented in the literature. It promotes better inventory management, increased revenues and decreased costs that can be shared across the chain as well as customer satisfaction (FAWCETT; MAGNAN; MCCARTER, 2008). Kumar and Banerjee (2014) also present as benefits of collaboration: improved visibility, higher service levels, increased flexibility, greater end-customer satisfaction, reduced cycle time and the ability to deal with high demand uncertainties. According to Ramanathan (2011), some of the purposes of collaboration are to improve overall business performance, reduce cost, increase profit and improve forecast accuracy.

Collaboration in supply chains has been largely studied in the past years. As discussed previously, collaboration may assume different forms and may be composed of different components and dimensions. In characterizing and conceptualizing collaboration, researchers have focused more on process integration (goal congruence, decision synchronization and resource sharing) and less on collaborative communication and joint knowledge creation (CAO; VONDEREMBSE; ZHANG, 2010). Kumar and Banerjee (2014) found out that after joint planning, companies directly concentrate on sharing resources for operations and then they focus on shaping a culture which is essential for facilitating other dimensions of the relationship.

Since collaboration can be carried out in several different manners, it is important to characterize its main components. In this sense, Table 2 depicts some components or dimensions of collaboration found in this literature review. As it can be seen, collaboration is formed by many different components, being Information sharing the most frequently cited in related studies. Other components that are cited by more than one study found in the literature review are decision synchronization, resource sharing, incentive alignment and the integration of supply chain processes.

Collaboration has heavily counted on information systems. Buyers and sellers have evolved into collaborators using four forms of electronic-transactional information sharing and collaborative processes. Kumar and Banerjee (2014) state that different types of systems and processes such as Vendor Managed Inventory (VMI) and Continuous Replenishment Planning (CPR) are implemented.

The first main technological form of transmitting and integrating data was Electronic Data Interchange (EDI), which has been used to transmit information such as purchase orders, invoices, material releases, shipping notices, and product inquiries electronically. As technology evolved, Efficient Consumer Response (ECR) solutions were driven by the need of establishing effective channel relationships. In this context, the VMI concept and its practices were introduced in the decade of 1990. VMI has existed in retailing before the growth of enabling technologies, and it has been perhaps the most widely known system for managing supply chains. In this practice, the replenishment decisions for all retailers are centralized at the upstream distributor or manufacturer. The manufacturer or distributor manages and monitors inventories of the wholesaler or retailer (ATTARAN; ATTARAN, 2007).

Table 2 – Collaboration's components

Constructs and Dimensions / References	(CAO; VONDEREMBSE; ZHANG, 2010)	(SIMATUPANG; SRIDHARAN, 2002)	(KUMAR; BANERJEE, 2014)	(DAUGHERTY et al., 2006)	(NYAGA; WHIPPLE; LYNCH, 2010)
Information sharing	✔	✔	✔	✔	✔
Goal congruence	✔				
Decision synchronization	✔	✔			
Incentive alignment	✔	✔			
Resources sharing	✔		✔		
Collaborative communication	✔				
Joint knowledge creation	✔				
Collaborative performance system		✔			
Integrated supply chain processes		✔		✔	
Joint planning			✔		
Joint problem solving and performance measurement			✔		
Collaborative culture			✔		
Jointly development of strategic plans				✔	
Joint relationship effort					✔
Dedicated investments					✔

Following this evolution, ever-increasing supply chain demands have led to the creation of Collaborative Planning, Forecasting and Replenishment (CPFR) (introduced in late 1990s), another SCM practice, which incorporates planning, forecasting, and replenishment under a single framework. The CPFR framework encourages all partners to share sales, inventory, forecast, and all related information to improve forecast accuracy. This information exchange is made possible through advanced technology in many retail sectors. CPFR extends VMI principles and is considered to be the latest stage in the evolution of supply chain collaboration (ATTARAN; ATTARAN, 2007). CPFR is a cohesive bundle of business processes whereby supply chain trading partners share information, synchronized forecasts, risks, costs and benefits with the intent of improving overall supply chain performance through joint planning and decision making (HOLLMAN; SCAVARDA; THOMÉ, 2015).

Collaboration and integration among companies in a supply chain or through dyadic relationships may be difficult to achieve due to a series of barriers. Although presenting clear benefits and outcomes, collaboration and integration usually face several barriers that impede them to be implemented fully and appropriately in supply chains.

Many supply chain collaborations fail due to incompatible corporate culture and the complexities involved (ZHANG; CAO, 2018). The single greatest barrier to supply chain collaboration is, according to the survey performed by Fawcett et al. (2008), inadequate information systems. Since collaboration is intrinsically information driven, inadequate or incompatible information systems are a critical barrier to collaboration and present a twofold dilemma. First, managing complicated supply chain networks requires collection and analysis of large amounts of data. Although technology advances have yielded great use of data warehouses that collect and store information, analyzing the data correctly (as to allow people to make good decisions) remains a difficult and complex task. Second, data only becomes valuable information when it is in the hands of the right people at the right time. If not all the participants of a chain can access needed information, opportunities for value savings cannot be evaluated and full benefits of integration will be difficult to attain. Because many firms are comfortable using their systems for only their own tasks, it is not surprising to see inconsistent information and technology systems as a barrier. Managers usually recognize technology, information, and measurement systems as major barriers to successful supply chain collaboration (FAWCETT; MAGNAN; MCCARTER, 2008). Besides, only a few companies are actually engaged in extensive supply chain integration (NÄSLUND; HULTHEN, 2012). Montoya-Torres and Ortiz-Vargas (2014) synthesize the principal barriers for the implementation of collaboration structures as being: lack of technology, confidence, decision about whom to collaborate with, misunderstanding of concepts, principles or elements of such collaboration, different goals among enterprises, excess of (unnecessary) information and lack of knowledge about how to use the information, inaccurate information systems and even resistance to changes.

Collaboration across boundaries is often very difficult to achieve due to cultural and structural barriers. Low levels of trust, for instance, prevent organizations from sharing proprietary information or resources (SOOSAY; HYLAND, 2015). In a study also aimed at identifying barriers to supply chain collaboration, Ramesh, Banwet and Shankar (2010) identified 13 barriers to inter-organizational collaboration. Among them, some can be highlighted such as lack of trust among partners, lack of collaborative and strategic planning, disparity in technological capability among partners and inadequate information sharing, which may result in behaviors that break down collaboration efforts. Collaboration among companies may even be more difficult to achieve in turbulent and strong competitive environments, whose characteristics are described in the next section.

2.3 Technological Dynamism and Competitive Intensity

Technological dynamism, also called technological turbulence, is defined as "the rate of technological change in the industry" (JAWORKSI; KOHLI, 1993). It may bring great opportunities (FERNÁNDEZ et al., 2010) and challenges for firms in that industry. In a rapidly changing technological environment, one can observe short product development cycles and fast technological obsolescence. These may create opportunities for firms to build superior competitive positions by changing or upgrading their products. Therefore, in such environments, firms are compelled to heavily rely on resource construction strategies (WU; LIU; ZHANG, 2017) and tend to develop innovative behaviors, act proactively and exhibit higher levels of risk in order to be more efficient and effective in the discovery and exploitation of new emerging opportunities (GARCÍA-VILLAVERDE et al., 2018). Besides, prior knowledge and competences become rapidly obsolete, so firms need to reconfigure their knowledge-base and build new competences quickly (CRUZ-GONZÁLEZ et al., 2015). Thus, employees with higher technological skills are absolutely essential to gain a competitive advantage (GARCÍA-VILLAVERDE et al., 2018).

Technological turbulence reflects the rate of innovation in the industry and pushes firms to adjust their new products development pace to cope with external competition (WU; LIU; ZHANG, 2017). In technologically turbulent environments, organizations are more likely to accept those supply chain technologies readily perceived as being useful due to compression of learning curves. In summary, the technological turbulence of the firm's environment facilitates or hinders the supply chain technology acceptance process (AUTRY et al., 2010). On the other hand, in non-turbulent or relatively stable technological contexts, the value of organizational resources, knowledge and capabilities keeps up for a longer time, so firms benefit from improving and exploiting their current knowledge (CRUZ-GONZÁLEZ et al., 2015).

Another important indicator of environmental dynamism, competitive intensity reflects the degree to which firms face competition within their industries (CHEN et al., 2015). Competitive intensity is defined as a situation where competition is fierce due to the presence of numerous competitors and the lack of opportunities for further growth (AUH; MENGUC, 2005). In a competitive context, one actor achieving a goal forecloses another from gaining his/her objective (MEDLIN; ELLEGAARD, 2015). Competitive intensity, in a particular sector, is determined by the number of firms in that sector and the market share of each competitor. The more competitors there are in a sector, the more intense is its competitive environment (JERMIAS, 2008), therefore, it refers to the degree of market competition faced by a firm. When the competition in a market is intense, the offerings that one competitor can provide can quickly be matched by others, and customers have many alternatives (JAWORKSI; KOHLI, 1993). In highly competitive environments, firms need to take advantage of existing market-driven competences to explore new and emerging market-driving possibilities (BOSO; CADOGAN; STORY, 2012).

The competitive intensity that firms face can be defined as the magnitude of effect that a firm has on its rivals' life chances. A weak competitor is one that harms its rivals' life chances only slightly, whereas strong competitors dramatically reduce their rivals' life chances (MARTIN; JAVALGI, 2016). In contrast, when competition in a market is mild, organizations may face less time pressure, and have sufficient time to integrate the diverse perspectives of different personnel and make decisions that are more rational in carrying out new product development (TSAI; HSU, 2014).

When competition is intensive, firms need to engage in risk-taking and entrepreneurial activities that require both learning and exploration. Such activities include innovating new products, exploring new markets, seeking novel ways to compete, and examining how to achieve differentiation (CHEN et al., 2015). We hypothesize the adoption of BDA Capabilities may bring such differentiation. This subject is presented in the following sections.

2.4 From Business Intelligence to Business Analytics and Big Data

Analytics, in broad terms, does not refer to a particular technology or method. Rather, it is a combination of multiple IT-enabled resources in order to gain information, answer questions, predict outcomes of problem solutions and support decision-making, consequently creating competitive advantage (DAVENPORT; JEANNE, 2007; DAVENPORT;

MORISON; HARRIS, 2010; TRKMAN et al., 2010). Analytics has been named differently over the years. Davenport (2014) states that the general activity of making sense of data has evolved from Decision Support to Business Intelligence (BI), Business Analytics (BA) and currently to Big Data and Big Data Analytics. In a similar way, Chen, Chiang and Storey (2012a) studied the evolution and focus of research from BI and BA to Big Data and found out that, in general, BI had the largest coverage and the longest history, appearing first in the early 1990s. BA and Big Data have only received more attention since 2007, with a steep increase in more recent years. Different goals characterized each stage of the historical evolution of Analytics. While BI mainly concentrates on reporting and extracting information from data, BA focuses on using statistical tools to support decision-making, prescribing and predicting actions. Big data, in turn, is related to working with huge amounts of data in various formats. BDA should be seen as a more general term that comprises the idea of applying analytical techniques to data sets that are so large and complex that require advanced and unique data storage, management, analysis and visualization technologies (CHEN; CHIANG; STOREY, 2012a).

The terms Business Intelligence, Business Analytics and Big Data are frequently used in the same context and sometimes are even used interchangeably. Chae and Olson (2013) state that BA and BI are viewed similarly in that both terms reflect a need for building and utilizing various analytical capabilities for organizational business process and decision support. Although they present common characteristics, it is possible to outline differences. Davenport (2014) differentiates these terms from a historical perspective as well as according to their main purpose. Business Intelligence focuses on tools to support data-driven decisions, with emphasis on extracting information and reporting. In the following years, Business Analytics received more attention by focusing on statistical and mathematical analysis for decision-making. Recently, the term Big Data has become more popular since very large, unstructured and fast-moving data are frequently available. The Big Data movement, like Analytics, seeks to glean intelligence from data and translate that into business advantage. However, there are three key differences, distinguishing Big Data from Analytics: volume, velocity (speed of data creation) and variety of data (different types and sources) (MCAFEE; BRYNJOLFSSON, 2012).

From a technical point of view, BI is related to a set of tools and technologies, such as data warehousing, online analytical processing (OLAP), data mining dashboards, analytic and reporting tools, among others that enable information gathering, recording, recovery, manipulation and analysis. Harrison et al. (2015) argue that there are two key types of BI: external and internal. External BI is based on data sourced from outside the organization, which clearly may have an impact on internal business decisions. External BI provides high-level data for strategic decision-making, from sources such as social media platforms, government reports or statistics, market reports and e-commerce, which allows an insight to competitors' performances and consumer trends. Internal BI, on the other hand, refers to the analysis performed using data from within the organization obtained from a wide variety of internal systems, such as CRM, financial systems or even the company website. In typical internal BI system architecture, the data are collected from internal operational source databases and imported into a data warehouse via a process called Extract, Transform and Load (ETL). Data are accessed in the data warehouse via internal BI tools and is displayed by front-end user applications. The typical components of internal BI architecture include the source data, the ETL process and the data warehouse. These components are considered the back-end infrastructure of an internal BI system. While internal BI can be seen as a principal source of competitive advantage for an organization, the benefits can only be appreciated when the outputs are fully integrated into the decision-making and business processes of the organization. BI competitive advantage has shifted from those who use their expertise to implement the technology, to organizations that use BI to increase sharing of information and knowledge as well as improve business processes (HARRISON et al., 2015).

In the late 2000s, Business Analytics came to be seen as the key analytical component in BI (CHEN; CHIANG; STOREY, 2012a). BA is not a technology, but a group of approaches, organizational procedures and tools used in combination with one another to gain information, and predict outcomes of problem solutions (TRKMAN et al., 2010). BA is defined by Jamehshooran (2015) as the practice of iterative, methodical exploration of an organization's data with emphasis on statistical analysis, used by companies committed to data-driven decision making. Côrte-Real et al. (2014) recognize the relationship between BI and BA and prefer to use the term Business Intelligence and Analytics (BI&A), which involve techniques, technologies, systems, practices, methodologies, and applications that analyze critical business data to help an enterprise better understand its business and market and make timely business decisions. Similarly, Davenport and Jeanne (2007) define BA as the use of data, analytical IT and fact-based management methodologies.

BA techniques can be categorized into three types of orientation: descriptive, predictive and prescriptive. Descriptive analytics may be considered the "simplest class of analytics”, and the vast majority of business analytics applications fall into this category. Its purpose is to describe and summarize events occurred in the past or events that are happening in the present, allowing analysts to condense significant amounts of data into useful information. Predictive analytics, on its turn, may be considered the next step in data reduction. It encompasses a group of methods that use statistical and other empirical techniques to study recent and historical data, thereby allowing analysts to predict future events based on past occurrences (BONNES, 2014). Probabilistic in nature, predictive analytics combine current and historical data from different organizational systems in order to make predictions about the future or unknown events. Prescriptive analytics, however, goes beyond descriptive and predictive analytics by using optimization and simulation algorithms to analyze data and transform them into recommended actions. It is, undoubtedly, a powerful foundation for decision management, helping managers to translate descriptive and predictive information into actionable, feasible plans of actions in the future.

More recently, Big Data and Big Data Analytics have been used to describe the data sets and analytical techniques in applications that are so large and complex that they require advanced and unique data storage, management, analysis and visualization technologies (CHEN; CHIANG; STOREY, 2012a). Kwon, Lee and Shin (2014) define BDA as technologies and techniques that a company can employ to analyze large scale, complex data for various applications intended to augment firm performance in various dimensions. Dubey and Gunasekaran (2015) present the term Big Data Business Analytics, which defined as an integration of data and technology that accesses, integrates, and reports all available data by filtering, correlating, and reporting insights not attainable with past data technologies. It is considered an emerging phenomenon that reflects higher dependence on data in terms of growing volume, variety and velocity. In this sense, Big data is defined as the dataset whose size is beyond the processing ability of typical database or computers. Four elements are emphasized in the definition, which are capture, storage, management, and analysis. The data-driven approach not only focuses on predicting what is going to happen, but also concentrates on what is happening right now and further getting ready for the future events.

Davenport (2014) defines Big Data as the collection and interpretation of massive data sets, made possible by vast computing power that monitors a variety of digital streams – such as sensors, marketplace interactions and social information exchanges – and analyzes them using “smart” algorithms. He emphasizes that Big Data is notably different from traditional information management and analytics because, instead of just creating reports or presentations that advise senior executives on internal decisions, big data scientists commonly work on customer-facing products and services. Tachizawa et al. (2015) define BDA as the process of examining large amounts of unstructured data to uncover hidden patterns, unknown correlations and other useful information.

Besides the challenge of working with huge amounts of data, the second obstacle is the velocity with which data is created and modified. Since the content of the big data keeps increasing over time, the targets of BDA also need to change with time. The variety of data, coming from different sources with different types, is a third obstacle (CHENG; QINGYU; QIN, 2012). Considering such challenges, Big Data has been initially characterized by the '3 Vs' (LYCETT, 2013):

- Volume: it is related to the key benefit of being able to process large amounts of data. Key considerations here relate to scalability, distribution, the ability to process such volumes of data and so on.
- Velocity: it is related to the importance of the data flow rate. Considerations here include the granularity of data streams, understanding what can be discarded and the acceptable latency in relation to data, decision making and action taking.
- Variety: it is related to the fact that data comes from many sources in many different forms – often unstructured, inconsistent and with errors.

More recently, value has emerged as a fourth 'V', since doing something valuable with the data is important and ultimately, the final purpose of all analytics effort. Other authors, like Cheng et al. (2012) include veracity - the uncertainty due to data inconsistency, incompleteness, and/or model approximations – as a fifth characteristic. Seddon and Currie (2017) included two additional dimensions in the definition of big data: variability and visualization. Variability refers to the dynamic opportunities that are available by interpreting big data, while visualization has to do with the representation of data in meaningful ways through artificial intelligence methods that generate models.

Big data technology needs to handle very large volumes of data that are constantly generated and flowing into the system at a very high velocity. Data can be machine-generated from "smart" devices that constantly log single actions and events. Some examples include data generated using radio frequency identification devices (RFID), smart meters, toll roads, click stream data, Global Positioning System (GPS) location data and social media uploads. Big data is also characterized by the variety of new and differing data types such as multi-media contents like text, audio, video, images, instant messages, Internet data from web pages, emails, documents and social media uploads like tweets and Facebook posts (HARRISON et al., 2015).

Supply Chain Analytics (SCA), understood as BA applied to the supply chain, extracts and generates meaningful information for decision makers in the enterprise from the enormous amounts of data generated and captured by supply chain systems. In a supply chain context, such data generated and collected across the supply chain is crunched, numbers are analyzed, and information is generated for decision makers (SAHAY; RANJAN, 2008). To Souza (2014), SCA focuses on the use of information and analytical tools to make better decisions regarding material flows in the supply chain. Schoenherr and Speier-Pero (2015) cite among primary barriers to the implementation of SCA, particularly predictive analytics, the inexperience of employees, the lack of integration with current systems, the costs of available solutions, change management issues and the lack of specific and appropriate analytics solutions for SCM.

Although a growing number of research has been made on SCA, Bonnes (2014) argue that this is still a relatively premature research area and that there is limited amount of research available on this subject, very much of it realized in the past few years. In fact, academic research into data science, predictive analytics, and big data in SCM has been scarce (SCHOENHERR; SPEIER-PERO, 2015). Recent review studies (CHEN; CHIANG; STOREY, 2012a; CÔRTE-REAL; RUIVO; OLIVEIRA, 2014) corroborate such statements by identifying that most research on BDA is aimed at characterizing the current research state with focus on technologies and systems and that most top-20 academic authors with BDA publications are from Information Systems and Computer Science. These authors have identified no emphasis on the application of Analytics in SCM contexts. Therefore, a study that unveils the many facets of the uses of BA and Big Data in SCM context seems to be highly recommended. In order to fully implement and take advantage of BDA, organizations must present several capabilities, described in the next section.

2.5 Big Data Analytics (BDA) Capabilities

A firm needs a blend of its financial, physical, human, and organizational resources to create a capability, which will be difficult to match by competitors (GUPTA; GEORGE, 2016). Business value is achieved when BDA (or BA) systems work in synergy with other organizational systems, which requires well-developed BDA capabilities and strong integration among BDA capabilities and other organizational resources. Cosic et al. (2015, p.

4) defined a BA capability as “the ability to utilize resources to perform a BA task, based on the interaction between IT assets and other firm resources”. Wang, Kung and Byrd (2016, p. 4) define a BDA capability as “the ability to acquire, store, process and analyse large amount of data in various forms, and deliver meaningful information to users that allows them to discover business values and insights in a timely fashion”. To Akter et al. (2016), a BDA capability is defined as the competence to provide business insights using data management, infrastructure and talent capacity to transform business into a competitive force.

The BDA capability is frequently identified as a higher-order and multidimensional construct, which indicates that several sub-dimensions would determine the initially identified primary dimensions (AKTER et al., 2016). Shuradze et al. (2016), for instance, conceptualize data analytics capabilities in three dimensions: infrastructure, personnel expertise and relationship infrastructure. By performing a literature review in big data, Akter (2016) identifies three key building blocks of BDA capabilities: organizational (management), physical (infrastructure) and human (skills or knowledge). Management capabilities involve BDA planning, investment, coordination and control. Technology capability comprises connectivity, compatibility and modularity. Finally, Talent capability includes BDA technology management knowledge, BDA technical knowledge, BDA business knowledge and BDA relational knowledge.

Table 3 summarizes the different constructs related to BDA capabilities, their dimensions and corresponding references, according to our literature review.

Table 3 – Dimensions of BA capabilities

Construct	Dimensions	References
Analytical Capabilities	Analytics of Plan Analytics of Source Analytics of Make Analytics of Delivery	(TRKMAN et al., 2010)
BA Capability	Governance Culture People Technology	(COSIC; SHANKS; MAYNARD, 2015)
Analytic Capability	Descriptive Diagnostic Predictive	(TAYLOR, 2015)
Data Analytics Capabilities	Infrastructure Personnel Expertise Relationship Infrastructure	(SHURADZE, GIORGI; WAGNER, 2016)
Big Data Analytics Capabilities	BDA Management Capability BDA Technology Capability BDA Talent Capability	(AKTER et al., 2016)
BDA Capabilities	Data Generation Capability Data Integration and Management Advanced Analytics Data Visualization Capability Data-driven Culture Cloud Computing Absorptive Capability	(ARUNACHALAM; KUMAR; KAWALEK, 2017)
BDA Capability	Tangible resources (Data, technology, basic resources) Human resources (managerial skills, technical skills) Intangible resources (data-driven culture and intensity of organizational learning)	(GUPTA; GEORGE, 2016)
BDA Business Analytics Capability	BDA Infrastructure Flexibility BDA Management Capabilities BDA Personal Expertise Capability	(WAMBA et al., 2016)
Big Data Analytics Capability	Tangible resources (infrastructure, information systems and data) Intangible resources (data-driven culture, governance, IT/business alignment) Human skills and knowledge (data analytics knowledge and managerial skills)	(MIKALEF et al., 2017)

Cosic et al. (2015) have identified a set of 16 BA capabilities that were grouped into four capability areas based on similarities: governance, culture, people and technology. Each capability area is further composed of 4 BA capabilities. The governance capability area is defined as the mechanism for managing the use of BA resources within an organization, and the assignment of decision rights and accountabilities to align BA initiatives with organizational objectives. The culture capability area is defined as the tacit and explicit organizational norms, values and behavioral patterns that lead to systematic ways of gathering, analyzing and disseminating data. Data-driven culture is a required intangible resource for organizations willing to make the best use of their big data. The data-driven culture scale can be used separately to capture the extent to which data drive decision making in organizations (GUPTA; GEORGE, 2016). The technology capability area is defined as the development and use of hardware, software and data within BA activities. A big data infrastructure includes data sources and a platform needed for collecting, integrating, sharing, processing, storing, and managing big data (GROVER et al., 2018).

The people capability area is defined as the skills and knowledge of the individuals within an organization who use BA as part of their activities. Wamba et al (2016) conducted a review on BDA capabilities which found out predominant dimensions, that is, management, infrastructure and personnel capabilities. Taylor (2015) defines analytic capabilities in function of its dimensions: descriptive, diagnostic and predictive. Finally, Trkman et al. (2010) define them in terms of the Supply Chain Operations Reference (SCOR) Model areas.

Human capabilities and competences for data analytics have been particularly explored in several studies (RAISINGHANI; MEADE, 2005; SANGARI; RAZMI, 2015; TAN et al., 2015). The need for such capabilities has increased so much that it has led to the creation of a broad range of analytical skills and roles within organizations. This demand has also led to an increase in the number of graduation and post-graduation courses (RANSBOTHAM; KIRON; PRENTICE, 2015). A recent study analyzed top MSc in Analytics programs and observed an almost homogeneous split of content across analytical and modeling tools, business processes, decision making and data management (SCHOENHERR; SPEIER-PERO, 2015), highlighting not only the importance of proficiency in tools but also of making sense of data and developing new insights from them. In addition, researchers call for data scientists and curriculums that address SCM problems (WALLER; FAWCETT, 2013).

Sharma et al. (2014) state that it is still vaguely understood how BDA can create value for organizations and, in fact, the thesis that BDA leads to value needs deeper analysis. Moreover, few studies explore data analytics from a capabilities perspective (SHURADZE, GIORGI; WAGNER, 2016). In this project, we hypothesize that BDA as an organizational capability might mediate the impact inter-organizational collaboration have on organizational performance, particularly for retail companies. Our research hypotheses are described in the next section.

2.6 Research Hypotheses

From the literature review carried out in this work, only studies that investigate the effect of BDA in just one organization were found. We conclude that research involving the adoption of BDA when two or more organizations collaborate is important and necessary. Since every firm serves as a producer as well as a user of information, they need to generate and analyze much of the information they use internally and share externally with respective partners, in addition to the information they receive from their partners (WU et al., 2016). In other words, companies need or are forced to develop collaboration strategies in order to analyze and work with data. Corroborating this assumption, in the context of a study on healthcare organizations, Wang et al. (2016) state that a prerequisite for implementing BDA successfully is that target organizations foster an information sharing culture. Without such a culture, data collection and delivery would be limited.

To the best of our knowledge, no previous research has developed a conceptual framework involving the constructs Inter-organizational Collaboration and BDA Capabilities. This knowledge gap is likely to constrain how we understand such capabilities and how organizations may use them to improve their performance. The fact that managers will typically need to negotiate across organizational boundaries to access assets they need to implement their BDA strategies motivates this research project. Furthermore, there will necessarily be heterogeneity in BDA capabilities within and between organizations (SHARMA; MITHAS; KANKANHALLI, 2014). Previous studies have already demonstrated that business analytics has a positive impact on organizational performance (TRKMAN et al., 2010). Authors found out that companies that support their analytical capabilities with good information systems are likely to be more capable of performing better. Plenty of previous studies have also shown the benefits and positive impacts of collaboration on different aspects of the supply chain performance and value creation (ATTARAN; ATTARAN, 2007; HORVATH, 2001; KUMAR et al., 2016; SCHOLTEN; SCHILDER, 2015; SOOSAY; HYLAND, 2015). In the existing literature, the success of collaboration practices is measured through different tangible and intangible attributes of sales performance such as profit, sales growth, improved production, reduced inventory and satisfaction of supply chain members (RAMANATHAN; GUNASEKARAN, 2014).

The role BDA Capabilities have in influencing, allowing or improving organizational performance - the extent to which a firm generates superior performance with respect to its competitors (GUPTA; GEORGE, 2016) - through inter-organizational collaboration is still unclear. This fact raises our first research hypotheses:

- H1: Inter-organizational collaboration has a positive influence on organizational performance.
- H2: Inter-organizational collaboration has a stronger positive influence on organizational performance when mediated by BDA capabilities.

Different studies have interpreted organizational performance as being closely related to financial performance (AKTER et al., 2016; JI-FAN REN et al., 2017; WAMBA et al., 2016; YU et al., 2018), which is related to customer retention, sales growth, profitability and return on investment (ROI). Due to the focus on retail companies, in this study, we consider other facets of organization performance, which are described as follows.

Nowadays, consumers have become value-driven (EL-ADLY; EID, 2016). The concept of value has meaningful implications for marketing as a discipline. Two dimensions have been developed: the economic (where value is linked to perceived price through what is known as transaction value) and the psychological dimension (where value relates to the cognitive and affective influences on product purchase and brand choice) (GALLARZA; GIL-SAURA; HOLBROOK, 2011). Value is directly related to the benefits one receives from a product or service and encompasses two domains – outcomes and processes. An outcome is valued to the extent that the object is useful, satisfies a need or solves a problem. It also encompasses processes which reflect the experience during the activity driving goal pursuit (CARLSON; O'CASS; AHRHOLDT, 2015). Perception of value with be defined based on Customer perception of value (CPV), which can be defined from the perspectives of money, quality benefit, and social psychology (KUO; WU; DENG, 2009). It is a trade-off between what they get (benefits) for what they give (price or sacrifice), but it is seen as all the factors, qualitative and quantitative, subjective and objective, that make up the complete shopping experience (EL-ADLY; EID, 2016; ZEITHAML, 1988). Moreover, CPV has been understood as the assessment the client does on that which is received as product performance or service when compared to the implied cost in comparison to other brands (VERA; TRUJILLO, 2013). The concept of consumer value is inextricably linked to major marketing-related constructs such as perceived price, service quality, or customer satisfaction. Value helps to explain different facets of consumer behavior that occur both before and after the purchase itself – for example – purchase intention, product selection, brand choice and repeat purchase (GALLARZA; GIL-SAURA; HOLBROOK, 2011).

Superior customer value is accomplished when a seller creates more value for the customer than the competitor does. The superior value can be understood as a competitive advantage (VERA; TRUJILLO, 2013). In the retailing industry specifically, it is mainly investigated in the product/brand and store contexts. Creating and delivering superior value and increasing customer satisfaction are crucial practices for retailers who want to achieve sustainable competitive advantage (EL-ADLY; EID, 2016). Empirical studies of the conventional retailers discovered that perceived value positively influences customer satisfaction in most cases (KUO; WU; DENG, 2009).

The Global Supply Chain Forum (GSCF) identifies eight key processes that make up the core of SCM: Customer Relationship Management (CRM), Customer Service Management (CSM), Demand Management (DeM), Order Fulfillment (OrF), Manufacturing Flow Management (MFM), Supplier Relationship Management (SRM), Product Development and Commercialization (PDC) and Returns Management (ReM) (CROXTON et al., 2001). The Order Fulfilment process usually demands the integration of people, processes, information, knowledge, and strategies across the supply chain between all points of contact and influence to facilitate the efficient and effective flows of material, money, information, and knowledge in response to customer needs. The OrF process deals with picking and shipping orders, so physical resources, such as, transported materials and transportation vehicles are involved. Physical logistics have become more dependent on information technologies, and these technologies can become enablers of further cooperative arrangements. The OrF process requires integration of the firm's manufacturing, logistics and marketing plans. Evaluating the logistics network has a significant influence on the cost and performance of the system. It involves all the steps from generating customer orders to picking and delivering them (CROXTON et al., 2001). This represents a potential application of BDA since it can be used to locate and track products through their transportation to final customers (DELEN et al., 2011; ZHONG et al., 2015). Improvements on the OrF process performance lead to the delivery of perfect orders. To Amer et al. (2010), a perfect order is a function of on-time delivery, quality of the delivered order, quantity of the delivered order and manifest accuracy (the delivered products are exactly the same requested by the client).

Comprehending financial performance, order fulfillment process performance and perception of value as components of organizational performance allows us to detail our first research questions as follows:

- H1a: Inter-organizational collaboration has a positive influence on organizational performance by increasing perception of value.
- H1b: Inter-organizational collaboration has a positive influence on organizational performance by increasing order fulfillment performance.
- H1c: Inter-organizational collaboration has a positive influence on organizational performance by increasing financial performance.

Dynamism is the rate of unpredictable change in a firm's environment and affects the ability of managers to predict related future events, their impact on the firm and responses to them. In a technologically dynamic environment, firms tend to develop an innovative behavior, act proactively and exhibit higher levels of risk in order to be more efficient and effective in the discovery and exploitation of new emerging opportunities (Rauch et al., 2009). (GARCÍA-VILLAVERDE et al., 2018). Technological dynamism, or technological turbulence, refers to the perception of swift changes in the technological development of the industry in which the firm is immersed. Technological turbulence assesses the extent to which the composition and preferences of an organization’s customers tend to change over time. (JAWORKSI; KOHLI, 1993). When the technological dynamism is higher, managers should try to strengthen their relationships with contacts that have the same values and norms as well as a common language and culture, and develop a higher trust between actors thereby decreasing monitoring costs and control mechanisms (GARCÍA-VILLAVERDE et al., 2018).

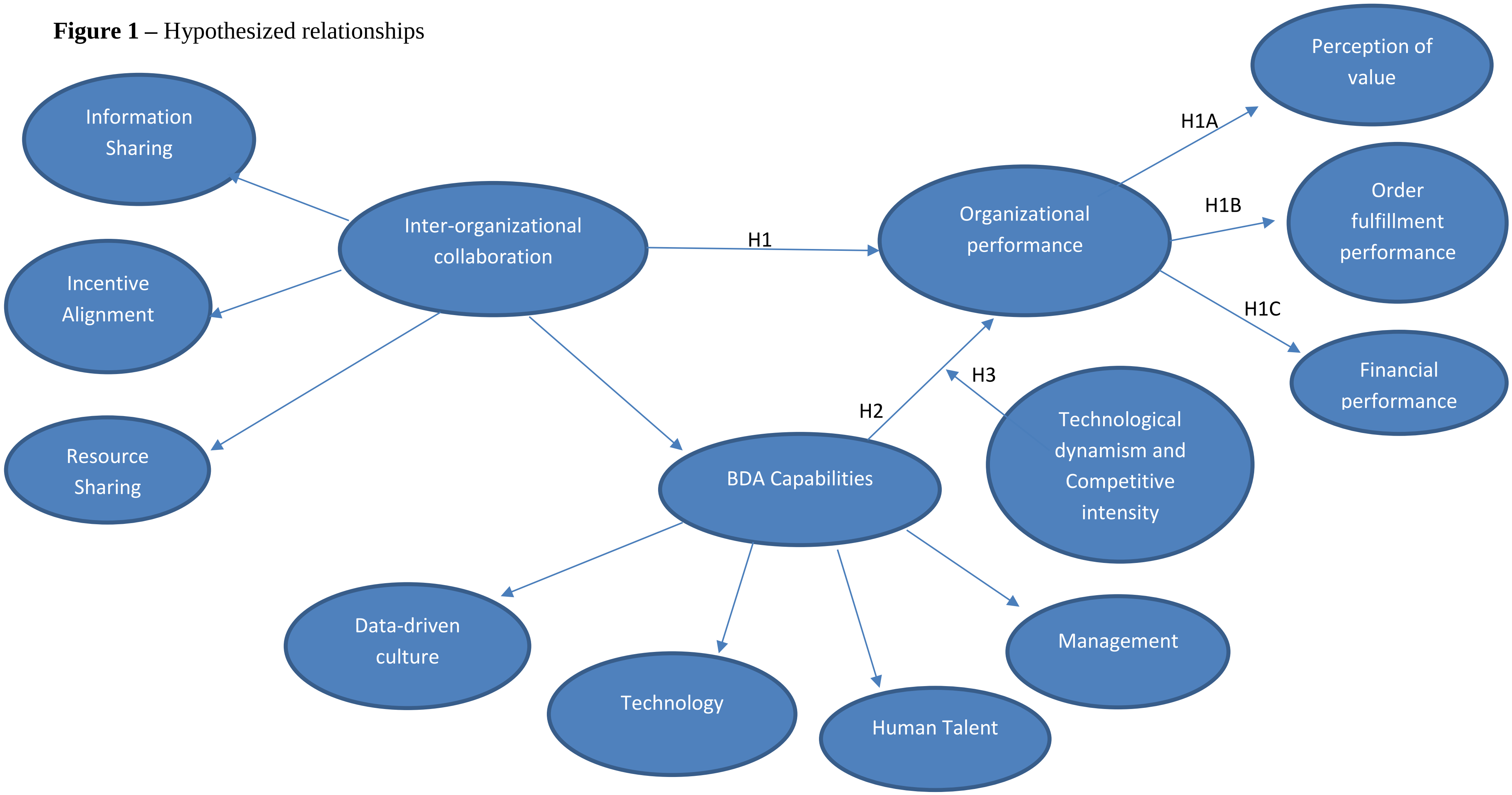
Competitive intensity, other component of environmental dynamism, is a situation where competition is fierce due to the number of competitors in the market and the lack of potential opportunities for further growth. As competition further intensifies, the results of a firm's behavior will no longer be deterministic but random as the behavior is heavily influenced by the actions and contingencies undertaken by competitors (MARTIN; JAVALGI, 2016). Conversely, as customers in a highly competitive market are much freer to change their suppliers, a firm that better satisfies customer requirements than its rivals in this market is likely to improve its performance (CHAN et al., 2012). Due to competition, customers also have more choices and can easily switch from one firm to another. In this case, the firm faces even more pressure, in deliberating over market newness, to provide the right product with the desired attributes to attract the targeted customers (FENG; HUANG; AVGERINOS, 2018). Intense competition is often associated with fierce price wars, heavy advertising and many competing product offerings. For example, firms in more technology-intensive industries, such as the electronic product industry, experience more rapid changes in technology development and face more uncertainty and more intense competition (CHEN et al., 2015).

On this basis, a hypothesis concerning the positive moderating effect of technological dynamism and competitive intensity on the relationship between inter-organizational collaboration and organization performance is thus proposed:

- H3: The mediator effect Big Data Analytics capabilities have on organizational performance is moderated by technology dynamism and competitive intensity.

According to the hypotheses presented, Figure 1 illustrates our original research model.

Figure 1 – Hypothesized relationships



This research extends the literature in big data by exploring the relationship between Inter-organizational collaboration, Big Data Analytics capabilities and organizational performance. Prior research has largely focused on the adoption of analytics in just one company alone, ignoring the influences collaboration might have on such relationships. Examining the mediating role BDA capabilities might have in modelling the impact of inter-organizational collaboration in organizational performance is important to both researchers and practitioners. We are not aware of any previous study that has investigated inter-organizational collaboration in contexts in which BDA initiatives are adopted. Finally, this research also contributes to retailing researchers by analyzing the effects inter-organizational collaboration have on organizational performance.

3. Research Methodology and Measure Development

We conceptualized the research model, which posits that inter-organizational collaboration, especially when mediated by BDA capabilities, influences organization performance. The research model also investigates whether technological dynamism and competitive intensity moderate this relationship. In this context, the unit of analysis is formed by managers, directors, supervisors who work with Supplier Relationships Management, Purchasing, IT and Marketing at Brazilian retail and wholesale firms surveyed in the study. These respondents were asked to share their perceptions of their firm's BDA capabilities, degree of inter-organizational collaboration, financial performance, order fulfillment process performance, and customer perception of value.

For this study, all measurement items were taken from our literature review and were adapted to fit the BDA context. Scales were customized to fit the context of our study to ensure that they were applicable and could be understood by informants of different companies, considering their size and comprehension of BDA practices. After the questionnaire was distributed and answered, we validated the hypothesized relationships using partial least squares (PLS) based structural equation modeling (SEM). Survey research is recommended for explanatory and predictive theory in order to ensure greater confidence in the generalizability of the results (WAMBA et al., 2016). Wang et al. (2016) corroborate the choice for such method stating that examining the impact of BDA capabilities on organization performance using quantitative analysis methods is necessary.

Table 4 presents the constructs assessed in this study, how they were defined from the existing literature and adapted to fit the purposes of this research. All constructs are considered reflective.

Measurement items for the constructs can be found in Appendix A. Items were measured on a five-point Likert scale ranging from (1) strongly disagree to (5) strongly agree, as used on previous studies (GUNASEKARAN et al., 2017). Aligned with the literature review performed, in order to measure BDA capabilities related to the use of technology, respondents were asked if they use different tools to visualize data, adopt cloud services and free software to process and analyze their data, if they have access to a great amount of both internal and external unstructured data to be analyzed.

Table 4 – Construct operationalization

Constructs	Definition	Derived from
BDA Capabilities – Human Talent	It refers to the BDA staff's professional ability (e.g., skills or knowledge) to undertake assigned tasks.	(WAMBA et al., 2016)
BDA Capabilities – Technology	It refers to the ability of the BDA infrastructure (e.g., applications, hardware, data, and networks) to enable the BDA staff to quickly develop, deploy, and support necessary system components for a firm.	(WAMBA et al., 2016)
BDA Capabilities – Managerial	It refers to the BDA unit's ability to handle routines in a structured (rather than ad hoc) manner to manage IT resources in accordance with business needs and priorities.	(GUPTA; GEORGE, 2016) (WAMBA et al., 2016)
BDA Capabilities – Data-driven culture	The extent to which organizational members (including top-level executives, middle managers, and lower-level employees) make decisions based on the insights extracted from data.	(GUPTA; GEORGE, 2016)
Inter-organizational Collaboration – Information sharing	The extent, to which a firm shares a variety of relevant, accurate, complete and confidential ideas, plans, and procedures with its supply chain partners in a timely manner.	(CAO; VONDEREMBSE; ZHANG, 2010)
Inter-organizational Collaboration – Incentive Alignment	The process of sharing costs, risks, and benefits among supply chain partners.	(CAO; VONDEREMBSE; ZHANG, 2010)
Inter-organizational Collaboration – Resource sharing	The process of leveraging capabilities and assets and investing in capabilities and assets with supply chain partners.	(CAO; VONDEREMBSE; ZHANG, 2010)
Organizational Performance - Financial performance	Firm's ability to gain and retain customers, and to improve sales, profitability, and return on investment (ROI).	(JI-FAN REN et al., 2017) (WAMBA et al., 2016)
Organizational Performance - Order process fulfillment performance	The level in which the organization can provide undamaged and flexible orders that are delivered on time, with no extra costs, accurate invoices and in the exact quantity requested.	(THIRUMALAI; SINHA, 2005) (AMER; LUONG; LEE, 2010)
Organizational Performance - Perception of Value	Difference between the highest price that consumers are willing to pay for a product or a service and the amount practically paid.	(THIRUMALAI; SINHA, 2005) (KUO; WU; DENG, 2009)
Technological dynamism and competitive intensity	Technological dynamism is the rate of technological change in the industry. Competitive intensity is the degree to which firms face competition within their industries.	(JAWORKSI; KOHLI, 1993) (GARCÍA-VILLAVERDE et al., 2018)

In terms of BDA capabilities concerning human knowledge, we aimed at measuring if people working with BDA have the necessary background, skills and experience to analyze and interpret data and if organizations invest on training employees for such skills. The managerial BDA capabilities involve being able to work together with other functional managers and/or with suppliers and clients as well as anticipating and considering their needs. Finally, BDA capabilities involve cultural organizational aspects such as considering data a valuable tangible asset and taking decisions based on data not on intuition.

Inter-organizational collaboration was defined in terms of information sharing, incentive alignment and resource sharing. Information sharing involves exchanging relevant, timely, accurate, complete and confidential information with supply chain partners. Incentive alignment is concerned with sharing costs, benefits, and risks with supply chain partners and having incentives commensurate with their investment and risk. We measure resource sharing as the ability of sharing technical support, equipment, financial and non-financial resources to manage collaborative processes.

Organizational performance was measured in terms of financial performance, order-fulfillment performance and customer-perceived value. In order to measure financial performance, respondents were asked if their organization improved customer retention, sales growth, profitability and market share during the last years relative to their competitors. This is in accordance with a recent study that suggested that firm performance is best measured relative to competition (WU; STRAUB; LIANG, 2014). To determine the order-fulfillment process performance, we assess if the organization's supply chain partners offer the ability of tracking orders, if their placing order process is easy, if they offer different shipping and handling charges and options, if they deliver orders on time, without damage and deliver exactly the products in the requested quantity. Perception of value sought to identify if the organizations' products meet their clients' expectations in a way the clients recognizes good value-added products and services for a reasonable price. If such expectations are achieved, clients will keep choosing this organization opposed to other companies.

The study used a cross-sectional e-mail survey in Brazilian retail and wholesale companies. The focus on the retail sector was given due to the promising future BDA has in this industry (GUTIERREZ, 2015). It is known that retailers can increase their operating margins by 60% through tapping into hidden values in big data (ZHAN et al., 2016). In fact, Germann et al. (2013) found out that, among industries surveyed in their research, the retail industry has been characterized as the one which has the most to gain from increasing their deployment of BDA. BDA can help retail organizations by allowing them to predict customer buyer behavior, to improve sales, market optimization, inventory planning and to work on fraud detection (KHADE, 2016).

Brazilian companies were chosen to be part of this study due to the rapid expansion in purchasing power of large emerging countries like Brazil, which is transforming these countries into the leading markets for consumer goods. The expansion of retailing activities and new opportunities will mostly occur in fast-developing, emerging countries (MIOTTO; PARENTE, 2015).

Fastoso and Whitelock (2011) have recently called for more research on Latin American countries stating that no attention has been specifically paid to this region in international marketing research, which is surprising given the economic importance of Latin America. Brazil is an emerging market and one of the highest priority markets for retail expansion. The Brazilian retail market is attractive for retailers considering the country's large population and the relatively stable macroeconomic conditions that had emerged in recent years (DE ANGELO; EUNNI; FOUTO, 2010). Besides, when compared to most other major emerging countries, Brazilians enjoy a higher purchasing power. Over 85% of its population lives in urban areas, the annual per capita income is about US$10,000 (according to the *Instituto Brasileiro de Geografia e Estatistica* (IBGE), and modern retailing occupies a dominant proportion of the Brazilian retail landscape (MIOTTO; PARENTE, 2015).

In a historical review of the retail industry in Brazil, Varotto (2018) states that technological innovations expand rapidly in the Brazilian retail, mainly through technologies that, on one hand, increase interactivity and facilitate the consumer buying process, on the other hand, make it possible to collect data and market information in real time through retailers. Among such innovations, the author highlights the use of RFID sensors and the adoption of the omni-channel model. Omni-channel retailing is a relatively recent phenomenon that has been transforming the retail landscape (LIM; SRAI, 2018). The concept of omni-channel accepts the inevitability of needing to employ multiple channels and is focused on integrating activities within and across channels to correspond to how customers shop (AILAWADI; FARRIS, 2017). An omni-channel strategy allows customers to shop across channels anywhere and anytime with a unique, complete and seamless shopping experience that eliminates the barriers between channels (RODRÍGUEZ-TORRICO; CABEZUDO; SAN-MARTÍN, 2017). Omni-channel integrates multiple channels to enable customers to simultaneously harness all available online and offline retail channels when shopping. It aims to deliver a seamless customer experience through the provision of a borderless cross-channel service system (LI et al., 2017). The adoption of omni-channel models in Brazil may favor collaboration and information sharing (PAYNE; PELTIER; BARGER, 2017).

The survey questionnaires were sent to key informants in the Information Technology, Purchasing, Supplier Relationship Management and Marketing areas. Data were analyzed using Partial Least Squares – Structural Equation Modelling (PLS-SEM) suitable for the analysis of the research model (HAIR, J.F. et al., 1998). The PLS-SEM model was conducted in a two-step process: evaluation of measurements and evaluation of the model. The results of the PLS algorithm are presented in the next section.

4. Results

4.1 Sample characteristics

The survey was administered to company owners, Chief Executive Officers (CEOs), directors, managers, coordinators and supervisors in Brazilian retail and wholesale organizations. Respondents were selected from Fundação Dom Cabral's mailing list, a prestigious business school (12nd in Financial Time's ranking[1]). Out of the 22.430 questionnaires distributed, 406 questionnaires were completed. If more than one respondent from the same company filled in the questionnaire, the one from the individual with the highest position in the company was kept. Due to this reason, 83 questionnaires were discarded. At the end, 323 questionnaires were considered usable for data analysis. The survey was available from 05/14/2018 to 08/30/2018. During this period, five reminders were sent. Table 5 represents the descriptive firm profiles.

Table 5 – Firm Descriptive Characteristics

		Number of Respondents	Percentage
Company type	Retailers	179	55.42%
	Wholesalers and Distributors	144	44.58%
Company size	Medium size	96	29.72%
	Large size	227	70.28%
Number of employees	51 – 100 employees	15	4.64%
	101 – 150 employees	31	9.60%
	151 – 200 employees	13	4.02%
	201 – 400 employees	50	15.48%
	401 – 600 employees	9	2.79%
	More than 600 employees	205	63.47%
Number of Stock Keeping Units (SKUs)	1 – 50 SKUs	2	0.62%
	51 – 100 SKUs	14	4.33%
	101 – 150 SKUs	3	0.93%
	151 – 200 SKUs	8	2.48%
	More than 200 SKUs	296	91.64%
Types of analyzed data	Activity data	281	87.00%
	Conversation data	11	3.41%
	Video and image data	15	4.64%
	Sensors data	16	4.95%

Medium-sized companies account for 29.72% and large-sized companies are 70.28% of the total number of participants. Most of the companies are considered large companies in terms of the number of employees. 4.64% of them have from 51 to 100 employees, 9.60% have from 101 to 150 employees, 4.02% have from 151 to 200 employees, 15.48% have from

[1] http://prod-upp-image-read.ft.com/8b1693b6-546c-11e8-b24e-cad6aa67e23e

201 and 400 employees, 2.79% have from 401 to 600 employees and 63.47% have more than 600 employees. Besides, 55.42% of the companies declare themselves to be retailers while 44.58% are considered distributors and wholesalers. Most of the companies commercialize a great deal of SKUs: 0.62% work between 1 and 50, 4.33% between 51 and 100, 0.93% between 101 and 150, 2.48% between 151 and 200 and 91.64% more than 200 SKUs. Considering data analysis efforts, 87.00% of the companies declare to analyze activity data (when online or physical human activities – software use, credit card use telephone use and so on are registered), while just 4.95% analyze sensors data, 4.64% analyze video and image data and 3.41% analyze conversation data (telephone conversations, SMS, e-mails, blogs comments, instant messages and social network posts).

We evaluated the PLS model using a PLS module for R called PLSPM (SANCHEZ, 2013) in two stages (ANDERSON; GERBING, 1988): examining the validity, unidimensionality and reliability of the measurement model and analysing the structural model. The first step, therefore, involves testing the measurement model and the second step tests the structural model and verifies the structural relationships represented by our hypotheses.

Before evaluating the measurement model, we performed two tests to detect Common Method Variance (CMV). CMV occurs when a systematic variance is introduced into the measures by the measurement technique. It is defined as the systematic error variance that is shared among variables which are measured with the same source or method (TEHSEEN; RAMAYAH; SAJILAN, 2017).

The first method applied in order to detect common method variance was Harman's Single-Factor Test. This is considered the most common test that is carried out by the researchers to examine CMV. A Harman one-factor analysis is a post hoc procedure that is conducted after data collection to check whether a single factor is accountable for variance in the data. In this method, all items from every construct are loaded into a factor analysis to check whether one single factor emerges or whether single general factor results in the majority of the covariance among the measures. If no single factor emerges and accounts for the majority of the covariance, CMV is not an issue (TEHSEEN; RAMAYAH; SAJILAN, 2017). In this study, the first unrotated factor captured only 20.97% of the variance in data, thus, no single factor emerged and the first factor did not capture most of the variance. Therefore, these results suggest that CMV was not an issue in this study.

The other method used to detect whether CMV was an issue in this study was the Marker Variable. In order to perform this test, a marker variable was included in the PLS model. An effective marker variable should share negligible or no substantively meaningful variance with the variables suspected of CMV bias (SIMMERING et al., 2015). In this study, the demographic items (company type, company size, number of SKUs, number of employees and role of the respondent) were used to form the marker variable. We followed the procedure recommended by Tehseen et al. (2017), which comprises the following steps: (1) observe the R^2 values of all endogenous latent variables in the hypothesized research model, (2) introduce the marker variable on all endogenous constructs, (3) observe the R^2 values of the endogenous constructs after adding the marker variable, (4) compare the R^2 values of the endogenous constructs before and after adding the marker variable. If a significant difference is observed in the R^2 value of any endogenous construct, then there is evidence of substantial common method bias. In this study, after performing such procedure, no significant difference was observed in the R^2 values after the introduction of the marker variable, showing that common method bias was not an issue.

Finally, we were also interested in assessing whether there were relevant differences between the sub-populations (groups) of retailers and wholesalers/distributors. In order to do so, we used the resampling parametric approach (SANCHEZ, 2013), which involved using a t-test based on bootstrap resamples. The procedure consists of separating the data into groups and then running bootstrap samples with replacement for each group. Path coefficients were calculated in each resampling. In this study, no statistically relevant differences were observed between the two groups, which means that the causal relationships observed are equally valid for both retailers and wholesalers.

4.2 Evaluation of the measurement model

The evaluation of the measurement model comprises unidimensionality analysis, convergent validity analysis and discriminant validity analysis, which are presented as follows.

4.2.1 Unidimensionality analysis

Among the tools available to check unidimensionality, we used Cronbach's alpha, Dillon–Goldstein's rho (composite reliability) and the first eigenvector. The traditional criterion for internal consistency is Cronbach’s alpha, which provides an estimate of the reliability based on the intercorrelations of the observed indicator variables (HAIR et al., 2017). The Cronbach's alpha is a coefficient that is intended to evaluate how well a block of indicators measure their corresponding latent construct. If a block of manifest variables is unidimensional, they have to be highly correlated, and consequently we expect them to have a high average inter-variable correlation (SANCHEZ, 2013). A block is considered as unidimensional when the Cronbach’s alpha is larger than 0.70 (TENENHAUS et al., 2005), although this minimum value is considered acceptable for existing scales and a value of 0.60 is deemed appropriate for newly developed scales (NUNNALLY, 1978).

Cronbach’s alpha is a conservative measure of reliability, that is, it results in relatively low reliability values. Another metric used to assess the unidimensionality of a block of indicators is the Dillon-Goldstein's rho which focuses on the variance of the sum of variables in the block of interest. This index is considered to be a better indicator than the Cronbach's alpha because it takes into account to which extent the latent variable explains its block of indicators (SANCHEZ, 2013; TENENHAUS et al., 2005). It measures composite reliability and it is the most robust measure of a construct's internal consistency because it prioritizes items by their reliability in estimating the measurement model (HAIR et al., 2017; WAMBA et al., 2016). A block is considered as unidimensional when the Dillon–Goldstein’s index is larger than 0.70.

The third metric involves an eigen-analysis of the correlation matrix of each set of indicators. The use of this metric is based on the importance of the first eigenvalue. A block is essentially unidimensional if the first eigenvalue of the correlation matrix of the block of indicators is larger than 1 (SANCHEZ, 2013; TENENHAUS et al., 2005).

Table 6 shows the results of the unidimensionality tests. It can be seen that all Cronbach’s alpha were greater that 0.70, except in the case of two constructs (BDA Capabilities – Technology and Order process fulfillment performance). In those cases, Cronbach’s alpha measures were superior to 0.60, but nevertheless considered acceptable, following an established rule of thumb for this test (TENENHAUS et al., 2005). All Dillon–Goldstein’s indices were superior to 0.70, as well as the first eigenvector values, all of them greater than 1.

Table 6 - Unidimensionality test results

Constructs	Cronbach's α	DG Rho	1st Eigenvector
BDA Capabilities (BDA)	0.9025803	0.9164670	6.054160
BDA Capabilities – Technology (CAT)	0.6704554	0.7860007	2.787216
BDA Capabilities – Human (CAH)	0.7657851	0.8423477	2.788064
BDA Capabilities – Managerial (CAM)	0.8679586	0.9045801	3.141673
BDA Capabilities – Culture (CAC)	0.8310043	0.8817117	7.429946
Inter-organizational Collaboration (INC)	0.8944625	0.9107135	2.411156
Inter-organizational Collaboration – Information sharing (INS)	0.7988965	0.8621692	2.585274
Inter-organizational Collaboration – Incentive Alignment (INA)	0.7980581	0.8617680	3.274545
Inter-organizational Collaboration – Resource sharing (RES)	0.8517253	0.8940951	3.001841
Organizational Performance (ORP)	0.7800633	0.8205853	4.076342
Organizational Performance - Financial performance (FIP)	0.8532862	0.9011715	2.781905
Organizational Performance - Order process fulfillment performance (OPF)	0.6410887	0.7642966	2.260725
Organizational Performance - Perception of Value (CPV)	0.7051580	0.8201167	2.152511

4.2.2 Convergent validity analysis

Convergent validity is the extent to which a measure correlates positively with alternative measures of the same construct. Indicators of a reflective construct are treated as alternative approaches to measure the same construct. Therefore, the items that are indicators of a specific reflective construct should converge or share a high proportion of variance (HAIR et al., 2017). To evaluate convergent validity of reflective constructs, two measures are frequently used: the outer loadings of the indicators and the average variance extracted (AVE).

High outer loadings of a construct indicate that the associated indicators have much in common, which is captured by the construct. The size of the outer loading is also commonly called indicator reliability. At a minimum, the outer loadings of all indicators should be statistically significant. The square of a standardized indicator's outer loading is referred to as the communality of an item. In this sense, communalities are just squared loadings. They represent the amount of variablity explained by a latent variable. A loading grater than 0.70 means that more than 50% of the variablity in an indicator is captured by its latent construct (SANCHEZ, 2013). The square of a standardized indicator's outer loading represents how much of the variation in an item is explained by the construct and is described as the variance extracted from the item. An established rule of thumb is that a latent variable should explain a substantial part of each indicator's variance, usually at least 50%. This means that an indicator's outer loading should be above 0.708 since this number squared equals 0.50 (HAIR et al., 2017).

Rather than automatically eliminating indicators when their outer loadings are below 0.70, researchers should carefully examine the effects of item removal on the content validity of the measurement models. In this sense, indicators with outer loadings between 0.40 and 0.70 should not be deleted when they contribute to content validity. Indicators with very low outer loadings (below 0.40) should, however, always be eliminated from the construct (HAIR et al., 2017). In this study, the indicator OPF7 ("*Our supply chain providers and partners do not usually return orders due to inconsistencies or damage*") has been removed because its outer loading was equal to 0.30. The majority of the measurement items presented outer loadings greater than 0.7. The indicators with outer loadings between 0.40 and 0.70 were maintained due to content validity.

Another common measure to establish convergent validity on the construct level is the Average Variance Extracted (AVE). This criterion is defined by the sum of the squared loadings divided by the number of indicators. Using the same logic as that used with the individual indicators, an AVE value of 0.50 or higher indicates that, on average, the construct explains more than half of the variance of its indicators (FORNELL; LARCKER, 1981).

The results of the convergent validity analysis are shown in Table 7.

4.2.3 Discriminant validity analysis

Discriminant validity is the extent to which a construct is truly distinct from other constructs by empirical standards. Thus, establishing discriminant validity implies that a construct is unique and captures phenomena not represented by other constructs in the model (HAIR et al., 2017). Traditionally, researchers have relied on two measures of discriminant validity. The cross-loadings are typically the first approach to assess the discriminant validity of the indicators. Specifically, an indicator's outer loading on the associated construct should be greater than any of its cross-loadings on other constructs, which indicate that items are more strongly related to their own construct than to other constructs (AKTER et al., 2016). Crossloadings values obtained in this study can be seen in Appendix B.

Table 7 - Loadings and AVE

	Items	Loadings	Communalities	AVE
BDA Capabilities – Technology	CAT1	0.7434583	0.55273018	0.4344154
	CAT2	0.5602166	0.31384263	
	CAT3	0.5454250	0.29748845	
	CAT4	0.4834896	0.23376219	
	CAT5	0.8119131	0.65920294	
	CAT6	0.7412596	0.54946575	
BDA Capabilities – Human	CAH1	0.7830706	0.61319962	0.5217440
	CAH2	0.6603459	0.43605665	
	CAH3	0.7006527	0.49091415	
	CAH4	0.7740379	0.59913469	
	CAH5	0.6851387	0.46941509	
BDA Capabilities – Managerial	CAM1	0.8170698	0.66760305	0.6799727
	CAM2	0.8099649	0.65604307	
	CAM3	0.8318432	0.69196311	
	CAM4	0.8339955	0.69554843	
	CAM5	0.8298830	0.68870580	
BDA Capabilities – Culture	CUL1	0.6841398	0.46804732	0.5938524
	CUL2	0.8312450	0.69096829	
	CUL3	0.7381827	0.54491368	
	CUL4	0.8019137	0.64306563	
	CUL5	0.7888392	0.62226730	
Inter-organizational Collaboration – Information sharing	INS1	0.7450274	0.55506584	0.5823820
	INS2	0.7297596	0.53254912	
	INS3	0.8614961	0.74217549	
	INS4	0.7968203	0.63492257	
	INS5	0.6687279	0.44719696	
Inter-organizational Collaboration – Incentive Alignment	INA1	0.7008560	0.49119910	0.6199800
	INA2	0.8367456	0.70014314	
	INA3	0.8084925	0.65366007	
	INA4	0.8362395	0.69929655	
	INA5	0.7453865	0.55560109	
Inter-organizational Collaboration – Resource sharing	RES1	0.7442253	0.55387131	0.6168855
	RES2	0.7599942	0.57759111	
	RES3	0.8229165	0.67719151	
	RES4	0.7846605	0.61569205	
	RES5	0.8124541	0.66008159	
Organizational Performance - Financial performance	OFI1	0.8166355	0.66689351	0.7247305
	OFI2	0.8784837	0.77173364	
	OFI3	0.8250167	0.68065260	
	OFI4	0.8829735	0.77964219	
Organizational Performance - Order process fulfillment performance	OPF1	0.5763264	0.33215208	0.3631693
	OPF2	0.7419093	0.55042935	
	OPF3	0.5824680	0.33926902	
	OPF4	0.5320931	0.28312302	
	OPF5	0.5049965	0.25502149	
	OPF6	0.6473184	0.41902106	
Organizational Performance - Customer Perception of Value	CPV1	0.6610714	0.43701541	0.5511054
	CPV2	0.6987653	0.48827300	
	CPV3	0.7688474	0.59112635	
	CPV4	0.8294619	0.68800698	

The Fornell-Larcker criterion is the second approach to assessing discriminant validity. It compares the square root of the AVE values with the latent variable correlations. Specifically, the square root of each construct's AVE should be greater than its highest correlation with any other construct. An alternative approach to evaluating the results of the Fornell-Larcker criterion is to determine whether the AVE is larger than the squared correlation with any other construct. The logic of the Fornell-Larcker method is based on the idea that a construct shares more variance with its associated indicators than with any other construct (HAIR et al., 2017). Discriminant validity is indicated if the AVE for each multi item construct is greater than the shared variance between constructs (FORNELL; LARCKER, 1981).

The results suggest that each construct is most strongly associated with its own indicators rather than with other constructs. The leading diagonal entry of Table 8 (first-order constructs), which represents the square root of AVE, is found to be greater than the inter-construct correlations. Hence, we can argue that our model demonstrates sufficient discriminant validity.

Table 8 - Loadings – First-order constructs

	INS	INA	RES	CAT	CAH	CAM	CAC	FIP	OPF	CPV
INS	**0,7631**									
INA	0,7122	**0,7874**								
RES	0,5422	0,6500	**0,7854**							
CAT	0,4445	0,4330	0,4057	**0,6591**						
CAH	0,3746	0,4230	0,3983	0,5720	**0,7223**					
CAM	0,3986	0,4120	0,2492	0,5510	0,6690	**0,8246**				
CAC	0,3226	0,2980	0,2524	0,5960	0,4970	0,6340	**0,7706**			
FIP	0,0816	0,1240	0,0518	0,3730	0,1870	0,3190	0,4420	**0,8513**		
OPF	0,3604	0,3130	0,3406	0,3430	0,3410	0,3150	0,2360	0,3443	**0,6026**	
CPV	0,2837	0,3440	0,3434	0,4630	0,3320	0,3200	0,4320	0,4731	0,4220	**0,7424**

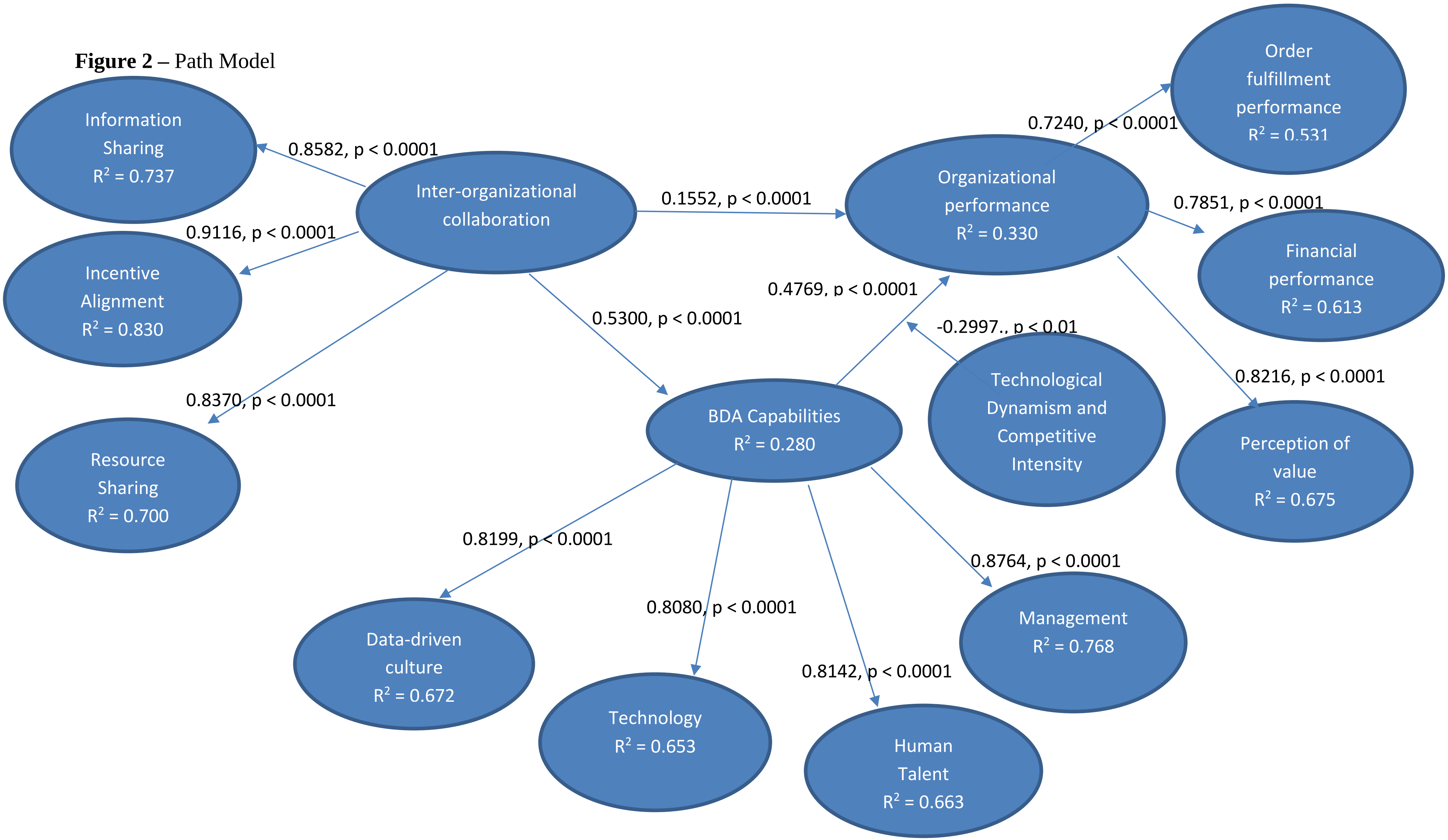
4.3 *Evaluation of the structural model*

After running the PLS-SEM algorithm, estimates were obtained for the structural model relationships, also called path coefficients, which represent the hypothesized relationships among the constructs. The standardized regression path coefficients may vary between -1 and +1. Estimated path coefficients close to +1 represent strong positive relationships, while path coefficients close to -1 represent strong negative relationships that are usually statistically significant. The path coefficients can be interpreted as the standardized beta coefficients in a regression equation, which means that when the exogenous construct is changed by one unit, the endogenous construct is changed by the size of the path coefficient when all other constructs and their path coefficients remain constant (HAIR et al., 2017).

The most commonly used measure to evaluate the structural model is the coefficient of determination, also called R^2 value. This coefficient is a measure of the model's predictive power and is calculated as the squared correlation between a specific endogenous construct and predicted exogenous variables. The coefficient represents the exogenous latent variables' combined effects on the endogenous latent variable, in other words, it represents the amount of variance in the endogenous constructs explained by all of the exogenous constructs related to it. In scholarly research that focuses on marketing issues, R^2 values of 0.75, 0.50, or 0.25 for endogenous latent variables can, as a rule of thumb, be respectively described as substantial, moderate, or weak (HAIR et al., 2017).

Figure 2 shows the path coefficients and R^2 values obtained in this study for the structural model.

Figure 2 – Path Model



The non-parametric approach of bootstrapping was used to evaluate the precision of the PLS parameter estimates. The bootstrap procedure is the following: M samples are created in order to obtain M estimates for each parameter in the PLS model. Each sample is obtained by sampling with replacement from the original data set, with sample size equal to the number of cases in the original data set (SANCHEZ, 2013). The bootstrap confidence interval allows testing whether a path coefficient is significantly different from zero. The confidence interval provides information on the stability of the estimated coefficient by offering a range of plausible population values for the parameter dependent on the variation in the data and the sample size. If a confidence interval for an estimated path coefficient does not include zero, the hypothesis that the path equals zero is rejected, and a significant effect is assumed (HAIR et al., 2017).

The results shown in Table 9 indicate that all path coefficients were significant with the bootstrapping test (p-values < 0.0001). For H1, the direct effect of inter-organizational collaboration on organizational performance was observed with a path coefficient of 0.1552. Hypotheses H1a, H1b and H1c were also supported with path coefficients greater than 0.7, which represents a strong relationship between organizational performance and its second-order constructs considered in this study. Hypotheses H2 and H3, which consider mediation and moderation effects, respectively, are discussed as follows.

Mediation occurs when a third variable, referred to as a mediator variable, intervenes between two other related constructs. More precisely, a change in the exogenous construct results in a change of the mediator variable, which, in turn, changes the endogenous construct. When mediation is present, the strength or even the direction of a relationship between two constructs depends on a third variable (HAIR et al., 2017).

Mediation analysis is eligible if the indirect effect is significant (CÔRTE-REAL; OLIVEIRA; RUIVO, 2017). In our study, we hypothesized that BDA capabilities mediate the relationship between inter-organizational collaboration and organizational performance. In order to analyze whether this mediation exists, we evaluated the size of the direct effect of inter-organizational collaboration on organizational performance that was absorbed by the mediator BDA. For this, we used the Variance Accounted For (VAF) to determine the size of the indirect effect in relation to the total effect. Evaluating the indirect effect presented in this research model, the indirect effect of BDA capabilities was calculated as 0.2527 ($0.5300 * 0.4769$) with a p-value < 0.0001 (direct effects are presented in Table 9). In addition, the Variance Accounted For (VAF) was calculated by taking the total indirect effect divided by the indirect effect plus the direct effect (0.2527/(0.2527 + 0.1552) = 0.6195)). According to Hair Jr. et al. (2017), VAF values greater than 0.80 indicate full mediation, values between 0.20 and 0.80 are indicative of partial mediation while VAF values lower than 0.20 indicate that no mediation exists. The VAF value obtained as 61.95% allows us to conclude that BDA capabilities are partial mediators of the relationship between inter-organizational collaboration and organizational performance.

Table 9 - Path coefficients and p-values for the structural model

	Path coefficients	Bootstrapping results (p-values)	Hypothesis no.	Hypothesis supported?
INC → ORP	0.1552	$p < 0.0001$	H1 – Direct effect	Yes
ORP → OPF	0.7240	$p < 0.0001$	H1a – Direct effect	Yes
ORP → FIP	0.7851	$p < 0.0001$	H1b – Direct effect	Yes
ORP → CPV	0.8216	$p < 0.0001$	H1c – Direct effect	Yes
INC → BDA	0.5300	$p < 0.0001$	H2 – Mediation effect	Yes (partial mediation)
BDA → ORP	0.4769	$p < 0.0001$	H2 – Mediation effect	Yes (partial mediation)
TDI → (BDA → ORP)	-0.2997	$p < 0.01$	H3 – Moderation effect	No

In our study we were also interested in verifying whether or not a moderating effect caused by technologial dynamism and competitive intensity existed on the relationship between BDA capabilities and organizational performance. A moderating effect is caused by a variable whose variation influences the strength or the direction of a relationship between an independent variable and a dependent variable (SANCHEZ, 2013). In order to assess this possible moderating effect, we have used the Product Indicator Approach. With this method, a new latent variable is created, which represents the interaction between the exogenous variable and the moderator variable. The new latent variable is created by multiplying the indicators of the independent latent variable by the indicators of the moderator latent variable. After running the PLS analysis including this new variable, we checked the obtained path coefficients and observed that the moderating product construct has a negative effect on the endogenous construct of Organizational Performance. We also observed that its associated bootstrap confidence interval contains the value of zero, having a non-signifficant effect. This means that the moderating effect of technological dynamism and competitive intensity on the relation between BDA capabilities and organizational performance is not significant. So, H3 was not supported.

The final measure of quality we examined was the Goodness-of-Fit (GoF) index, which attempts to account for the overall quality at both the measurement and the structural models. Basically, the GoF index assess the overall prediction performance of the model by taking into account the communality and the R^2 coefficients. In this study, GoF was calculated as the geometric mean of the average communality and the average R^2 value. At last, a GoF index of 0.54 (54%) was obtained.

5. Discussions

The results of this study provide strong evidence supporting our model that improving inter-organizational collaboration and BDA capabilities can positively influence organizational performance, more specifically, financial performance, order process fulfillment performance and perception of value. The results show that inter-organizational collaboration is able to explain 33.0% of the direct variance of organizational performance. This is in accordance to a previous study that has stated that BDA solutions enhance the financial performance of a firm, as far as customer retention, sales growth and profitability are concerned (RAGUSEO; VITARI, 2018). In addition, Muller et al. (2018) found out that BDA assets are associated with an average of 3 to 7% improvement in firm productivity.

The companies that participated in this research have demonstrated performance improvement in the last few years. 59.75% of the organizations improved customer retention, 59.44% improved sales growth and 62.23% of the organizations improved profitability during the last 2 years relative to their competitors. Besides, 67.49% of the organizations improved their market share during the last 3 years relative to their competitors.

Among the several paths through which BDA can lead to improvements on organizational performance, our study shows that developing inter-organizational collaboration and BDA capabilities can lead to improvements on perception of value, financial performance and order fulfillment process performance. Moreover, to the best of our knowledge, this is the first study to show the importance of the mediating effects of BDA capabilities on such dimensions of the organizational performance. Ji-fan Ren et al. (2017) argue that, although firms spend millions of dollars on BDA to enhance business value and firm performance, studies on BDA to improve business outcomes show mixed results. Therefore, theories explaining how BDA can improve performance are critical current challenges. As follows, we discuss the results of this study in terms of its hypothesis.

The hypothesis that inter-organizational collaboration contributes to organizational performance was supported in this research (RQ1). In our study, inter-organizational collaboration is understood as information sharing, which is considered by Ramanathan and Gunasekaran (2014) the core element of collaborations, incentive alignment (mostly sharing of costs and risks) and resource sharing. Our results show that companies already have an information-sharing culture when it comes to non-confidential information. However, companies do not seem to have implemented practices that go beyond the primary level of information sharing. Respondents state that they exchange relevant (72.45%) and timely (68.73%) information, with their supply chain partners. Nevertheless, only 26.63% exchange confidential information; just 22.60% share costs while 33.75% share benefits and 28.79% share risks. In terms of resource sharing, only 34.06% share technical support and 21.67% share equipments. We could infer that organizations in this study are still on operational levels of collaboration since strategic partners share both strategic and operational information and resources, whereas operational partners share only operational information and resources (DU et al., 2012).

Although companies are still reluctant somehow in developing trustful relationships with their supply chain partners, our results show that the level of Inter-organizational collaboration they already exhibit positively influences organizational performance. We believe that if companies continue on developing more trustful and thorough relationships with their partners, inter-organizational collaboration might still have an even greater impact on organizational performance. This is corroborated by Li et at. (2015) who found out that the relationship length and supplier trust can strengthen the effectiveness of information sharing, especially regarding risks. The results also corroborate the work of Narayanan et al. (2015), who found out that organizations need to establish a certain level of collaboration before its positive impact can be realized.

Previous studies point out different barriers to collaboration. Although inter-organizational collaboration can be beneficial for organizations, engaging in collaborations is a time-consuming and costly process, and the associated risks are numerous. They range from leakage of proprietary information, to brand dilution, and to inadvertent and gradual dependence on alliance partners (MOURI; BINDROO; GANESH, 2015). In this sense, sharing private information has been identified as prerequisite for collaboration and, at the same time, as one of its major obstacles (PIBERNIK et al., 2011). Companies are often not willing to engage in collaborative practices mainly due to their reluctance towards sharing sensitive data (PIBERNIK et al., 2011). This may be specially true in the retail market, where BDA may involve sharing of customer data, customers' privacy is a great concern. One of the uses of BDA in this sector is the personalization of services and offers. By getting to know who their client is through the analysis of data, companies can offer more personalized services and products. However, the pursuit of identification and personalization of users poses a risk to privacy. Users can easily perceive this insight as invasive, unexpected, and unwelcome (WACHTER, 2018). If customers see the collection of their personal information as excessive, their perceptions of the retail stores and their intention to return to the stores may be jeopardized (ALOYSIUS et al., 2016). Therefore, in the context of collaboration, one major challenge is to decide how to share and protect information simultaneously, that is, to protect confidential information while sharing necessary information with partners (ZENG et al., 2012).

We found out that one of the benefits of improving organizational performance is improving the performance of processes related to order fulfillment. We believe research on order fulfillment will continue to grow since a potential application of BDA is to locate and track products through their transportation to final customers (BARBOSA et al., 2017). The patterns obtained from the large amounts of data can help improve transportation systems in terms of minimising traffic congestion by providing alternative routes, reducing the number of accidents, optimising freight movements and reducing supply chain wastage (HASHEM et al., 2016). The demands and requirements of city logistics are changing through innovations in technologies with smart computing, which makes the real-time tracking of vehicles possible. Vehicular traffic information is the most significant source of information in a smart city (RATHORE et al., 2016). In this context, a yet greater number of studies involving smart cities will be executed. The extent to which smart cities-Big Data implementation impact on SCM is still to be investigated. Smart cities generate several opportunities to SCM. For example, they can provide open data systems based on diversified sources (e.g. public data, citizen produced content or urban sensors). This can be particularly critical in the mobility aspects of the supply chain (TACHIZAWA et al., 2015). A number of current and upcoming technologies such as RFID, IoT and future internet technologies contribute extensively in making the cities smarter. Increasing presence of these technologies is causing the generation of a larger volume of data. More studies concerning Big Data logistics involving the modelling and analysis of urban transport and distribution systems through data sets created by GPS, cell phone and transactional data of company operations (MEHMOOD et al., 2017) are demanded.

Our second hypothesis explored the mediating effect of BDA capabilities on the relationship between inter-organizational collaboration and organizational performance (RQ2). To create a BDA capability, a firm needs a unique combination of different capabilities that generates a firm-specific BDA capability. Creating a BDA capability is a complex process because it requires several tangible and intangible resources, human skills, infrastructure and also managerial skills. So, it is imperative for managers to have a sharp understanding of how and where to apply the insights extracted by their technical teams (GUPTA; GEORGE, 2016). Our study recommends that equal attention should be paid to all the dimensions of BDA capabilities, although management capabilities seem to have a greater influence on the outcomes of this research.

Previous studies have put emphasis on different BDA capabilities. Grover et al. (2018) state that the most critical element is the human talent because expertise and experience are needed to design and implement BDA strategies. According to the authors, it is impossible to develop and carry out a BDA strategy without the right group of skilled big data experts. Anwar et al. (2018) found out that technological capabilities have signficant positive relationship with firm performance. Their study was carried out in China, where firms give considerable attention to technological capabilities because it provides prominent advantage and success. In countries like Brazil, where talent skills are scarce, not only data scientists are needed, but they should also have the competences to analyze and interpret data and turn them into value. Muller et al. (2018) state that only firms with substantial data assets and access to professionals with big data skills are able to profit from big data investments because BDA solutions require complementary IT assets and capabilities.

A challenge in this field is the lack of knowledgeable experts in both SCM and BDA. Professionals need to possess both skills related to technology as well as to specific business domains (BOSE, 2009; CHEN; CHIANG; STOREY, 2012b; RICHEY et al., 2016; SCHOENHERR; SPEIER-PERO, 2015). Some firms face the problem of a lack of knowledgeable and qualified scientists available to analyse the data (DUBEY; GUNASEKARAN, 2015; RICHEY et al., 2016; WIXOM et al., 2014). Recent research has shown that inadequate staffing is among the leading barriers to BDA (DEBORTOLI; MÜLLER; VOM BROCKE, 2014). The skills needed most, as identified by Schoenherr and Speier-Pero (2015), come from the disciplines of forecasting (qualitative and quantitative), optimisation, statistics (methods of estimation and sampling), economics (determining opportunity cost), mathematical modelling and applied probability.

It is a challenge to recruit fresh talent and train current employees in big data-specific skills, since working with Big Data requires new kinds of technical and managerial abilities, which are not commonly taught in universities (GUPTA; GEORGE, 2016). A chronic shortage of consumer data scientists exists, as marketing departments in business schools have been slow to design curricula to generate such talent (VERA-BAQUERO et al., 2015). Educational programmes should provide an analytical foundation to complement the business theory foundation students already receive in universities (HAZEN et al., 2016). Lots of universities and research institutes have even set up undergraduate and/or postgraduate courses on data analytics for cultivating talents, including data scientists and data engineers (JIN et al., 2015). A survey performed in 2013 identified 131 full-time BI/BA university degree programmes. Besides, 75% of employers preferred to hire students with formal BI/BA degrees or majors (WIXOM et al., 2014). While the computing technologies required to facilitate these data are keeping pace, the human expertise and talents business leaders require to leverage BD are lagging behind, this proves to be another big challenge (SIVARAJAH et al., 2017).

The skillset of a data scientist is at the convergence of three expertise domains that are mathematics, computer science and business (CARILLO, 2017). In this sense, what we have called Management capabilities and Human talent capabilities comprise what is expected from a data professional nowadays. BDA specialists must have substantial industry knowledge in order to make sense of statistical analyses and communicate effectively with business colleagues. Knowledge in NoSQL databases and software engineering and programming are the most highly demanded areas of technical competency (DEBORTOLI; MÜLLER; VOM BROCKE, 2014). Dubey and Gunasekaran (2015) categorized the BDA skill set in hard and soft skills. The authors identified as hard skills: Statistics, Forecasting, Optimization, Quantitative finance, Financial accounting, Positive attitude, Multivariate statistics, Multiple criteria decision making, Marketing, Research methods and Finance. Soft skills were identified as being Leadership ability, Team skills, Listening skills, Learning, Communication skills, Interpersonal skills, Patience and Passion. Analysts should be competent in four distinct but equally important skill sets: technical knowledge, technology management knowledge, business knowledge and relational knowledge (AKTER et al., 2016). Programming and statistical expertise are the foundation for data scientists but a strong background in business and strategy can help raise a younger scientist's career to the next level (DEBORTOLI; MÜLLER; VOM BROCKE, 2014). To Alharthi et al. (2017), the key skill required for big data is knowledge in big data platforms and technologies. Secondary skills would include statistics, machine learning, predictive analytics, data visualization and decision making models. Data scientists should also have a problem-solving orientation and be capable of independent working (VIDGEN; SHAW; GRANT, 2017).

The data scientist seems to be a hybrid of a computer scientist and a statistician, yet many more business-related authors state that, in the world of big data, one cannot separate data processing from analysis or from domain knowledge (DEBORTOLI; MÜLLER; VOM BROCKE, 2014; WALLER; FAWCETT, 2013). To develop relevant analytic insights, analysts must integrate their analytics capabilities with the domain-specific knowledge of decision makers (KOWALCZYK; BUXMANN, 2015). The world of data scientists needs to be connected to that of domain experts (VIAENE, 2013). Effective decision support with BDA requires analysts to have a higher level of specialization in analytics, which is different from the domain knowledge of decision makers, and this leads to further challenges. So, analysts are supposed to provide transparency and alignment with decision makers regarding their procedures and goals in deriving analytic device (KOWALCZYK; BUXMANN, 2015). Mutual trust and a good working relationship between big data managers and other functional managers will likely lead to the development of superior human big data skills, which will be difficult to match by other firms (GUPTA; GEORGE, 2016). Vidgen et al. (2017) state that a data scientist needs to be a "bricoleur" and have the ability to work cross-functionally across business silos.

The extent to which BDA capabilities might have a positive impact on organizational performance may be constrained by the observed level of inter-organizational collaboration. In this context, the different forms of collaborative agreements with regards to data exchange and their resulting business value are posed as an area of increased interest. It is highly probable that the boundaries of the insights that firms can develop, and, subsequently, the types of competitive actions that they can launch, are restricted by the availability of data (MIKALEF et al., 2017). Companies should work on obstacles and barriers to improve information sharing, which should be done along with developing BDA Capabilities.

Our study also investigated whether technological dynamism and competitive intensity moderate the effect of BDA capabilities on organizational performance (RQ3). Competitive intensity has been widely used as a moderator in literature (CHAN et al., 2012; CHEN et al., 2015; FENG; HUANG; AVGERINOS, 2018; JERMIAS, 2008; MARTIN; JAVALGI, 2016; TSAI; HSU, 2014) as well as Technological Dynamism (CRUZ-GONZÁLEZ et al., 2015; FERNÁNDEZ et al., 2010). However, this role has not been examined in the context of BDA capabilities and organizational performance yet. The results of this study fill this gap by suggesting that such moderating effect does not exist.

We found out that the Brazilian retail sector is characterized as highly dynamic in terms of technological advances as well as highly competitive. 90.40% of the respondents agreed that technology is rapidly changing in the retail sector while 96.28% believe that such technological changes bring great opportunities. In terms of intense competition, 89.47% of the survey respondents agreed that there are qualified competitors in the market, 94.12% state that price competition is frequent while 91.02% believe there are price wars in retailing.

Despite such characterization, the technological dynamism and competitive intensity do not impact the effect BDA capabilities have on organizational performance. At first, it was expected that in highly technologically dynamic and competitive markets, BDA capabilities would greatly improve organizational performance. Such expectation was grounded on the literature review carried out. Terawatanavong et al. (2011) explain that when technological turbulence is relatively minor, a close bond between the buyer and supplier acts as a buffer to the environmental uncertainty. In this case, both partners are able to leverage their resources to cope with difficulties arising from the low level of technological turbulence. However, as technological turbulence becomes increasingly dramatic, the close relationship becomes an obstacle to change and learning. The authors say that managers must be aware of turbulence and be alert in managing relationships with partners if technological turbulence arises. Besides, in highly dynamic and turbulent environments, the value of insight may be diminished by scarce resources or competitors launching competitive actions in short cycles (MIKALEF et al., 2017). The recent study conducted by Muller et al. (2018) showed that BDA resources are associated with higher productivity for firms in highly competitive industries, while for firms in non-competitive industries no measurable impacts were observed. Authors claim that this could be due to the fact that BDA enables companies in highly concentrated markets to eliminate slack, for example, by automating routine decision-making tasks or designing products and services that offer superior value to the customer and are distinct from the competition.

Although our results are distinct from the ones observed by Muller et al. (2018), it is important to highlight important differences between these two studies. The authors focused on technical BDA resources only (hardware and software licenses) and did not explicitly measure other types of BDA resources, such as BDA-related human resources or managerial capabilities, which were included in our study. Besides, they investigated only companies that adopted BDA solutions from one particular vendor, one specific sector (manufacturing industries) and only companies that are publicly traded on U.S. stock exchanges. The authors themselves claim that future research should aim to simultaneously quantify the business value of technical, human, and managerial BDA resources, which is towards the direction our research points out.

Besides, we could infer that the Brazilian companies which participated in this research could develop a more data-driven culture since they implement data analysis on just a few specific types of data. Almost 90% of the companies claim to analyze activity data (when online or physical human activities – software use, credit card use telephone use and so on are registered), while less than 5% analyze conversation data (telephone conversations, SMS, e-mails, blogs comments, instant messages and social network posts), video and image data and sensors data. Supply chains data require advanced data storage systems and are heavily dependent on major investments in technological infrastructure to use BDA techniques. The technologies that are available for supply chain data collection and storage include ERP, inter-organisational systems and RFID. With the increase in the use of IoT devices, more data will be generated. Sensors and embedded technology now enable the transmission of real-time data from wireless networks which will lead to the co-creation of new real-time knowledge among customers and vendors (BARBOSA et al., 2017). Companies which use the IoT can gather data about how their products behave and interact, and can then use it to understand and predict future behaviours. Using data from sensors, companies can optimise performance and can drive profitable outcomes for themselves through better user experiences. Companies can use the data collected from sensors to change the way that they design, upgrade and maintain devices in the field (UDEN; HE, 2017). We believe that when some companies are able to better explore and analyze different types of data, they will distinguish themselves from their competitors and maybe the technological turbulence and intense competition they face will moderate how their BDA capabilities affect their performance.

Our results are grounded in the RV theory. This theory states that critical resources are not solely housed within a single firm, but may span firm boundaries and be embedded in interfirm routines and processes, or in other words, the supply chain (GOLD; SEURING; BESKE, 2010). According to RV, resources and capabilities are more valuable when combined in unique ways, resulting in relational rents, i.e. super normal individual firm profits. The theory postulates that there are instances when this competitive advantage can only be generated through joint contributions specific to the collaborating organizations (BENSTEAD; HENDRY; STEVENSON, 2018).

According to the RV, firms who combine, share and invest in relationship-specific assets, substantial knowledge, complementary resources, and effective governance may realize relational rents that cannot be generated by either firm in isolation. A relational rent is a supernormal profit jointly generated in an exchange relationship that cannot be generated by either firm in isolation and can only be created through exclusive joint contributions of specific alliance partners (DYER; SINGH, 1998). As so, achieving relational gains and competitive advantage depends directly on the development and maintenance of relational capabilities This suggests that activities of supplier development, in which firms convert general-purpose assets such as money, people skills or managerial knowledge into relationship-specific assets, obviously represent a rent-generating process in accordance with this theory (PROCH; WORTHMANN; SCHLÜCHTERMANN, 2017).

Dyer and Singh (1998) identify four determinants of inter-organizational competitive advantage: (1) relation specific assets; (2) knowledge-sharing routines; (3) complementary resources and capabilities; and (4) effective governance and time-compression diseconomies, identified as factors for sustaining competitive advantage on a firm level, also apply on a dyadic or network level.

The choice of using the RV in this thesis answers a call for more opportunities to develop studies under such theory (BARBOSA et al., 2017), since working with BDA in supply chain contexts implies integrating systems that are not necessarily compatible or have the same data formats. This involves concerns on data interoperability and integration in a supply chain that implements data analytics initiatives. In this way, companies need to develop more integrated mechanisms for knowledge and information sharing, share assets (equipment and personnel) and complement their weak capabilities with strong capabilities found in partner companies.

According to the RV theory, the employment of effective governance may influence the willingness of firms to engage in supplier development initiatives, a condition that could be an important source of competitive advantage (DYER; SINGH, 1998). The theory states that the adoption of safeguard mechanisms encourages companies to make higher investments in relationship-specific assets. According to the authors, when firms are able to align a certain level of relationship-specific investments with appropriate safeguard mechanisms, they could enhance efficiency and effectiveness of supplier development activities. Although firms can select a variety of safeguard mechanisms, legal contracts are typically considered the primary formal means for safeguarding transactions. If one firm violates the terms of the contract, the other has the right to go to a third party to impose corrective action (PROCH; WORTHMANN; SCHLÜCHTERMANN, 2017). In this context, Hahn and Gold (2014) considered the existance of both formal and informal governance mechanisms. Formal mechanisms included formal contracts used for strategic alliances while informal mechanisms include trust, mutual goals and support from top management. Based on the RV theory, the results of this research show that companies need to invest on developing their governance mechanisms, both formal and informal ones. Considering that companies usually do not share private and sensitive information, nor costs, benefits and risks, nor equipment and processes, formal governance mechanisms could be useful in order to establish guidelines and rules so that privacy is not violated.

6. Conclusions

The objective of this research was to analyze how collaboration among companies, especially when supported by BDA capabilities, contributes to increasing organizational performance. We were also interested in analyzing how the turbulent environment in which organizations are influences organizational performance. In a study conducted with medium and large-sized Brazilian retail companies, we have found out that Inter-organizational collaboration has a direct effect on organizational performance as well as that BDA capabilities mediate such relationship. No moderating effect of technological dynamism and competitive intensity was observed.

This research has contributions both to scholars and to practitioners. The proposed original model extends the literature exploring the relationship between collaboration, BDA capabilities and organizational performance. To our knowledge, no prior research has studied these relationships. The results showed that BDA capabilities have a partial mediating effect on the relationship between Inter-organizational collaboration and organizational performance. Besides, this research also examines the moderating effect the technological turbulent environment in which retail organizations are could have on the relationship between inter-organizational collaboration and organizational performance. The study has shown that, although these companies are in a highly competitive and turbulent environment, such environment does not moderate the effect BDA capabilities have on the relationship between Inter-organizational collaboration and organizational performance. This could be explained by the fact that organizations still analyze few different types of data, which could cause low differentiattion among their competitors. When companies are able to develop different BDA capabilities that allow the analysis of different data types (video, images, sensors data), they might distinguish themselves from competition in a way the technological turbulence and intense competition they face would moderate how such BDA capabilities affect their performance.

For practitioners, this study stimulates organizations to invest on the development of their BDA capabilities to improve organizational performance in order to achieve competitive advantages. Besides, this research shows that organizations should invest on the development of collaboration relationships with partners and providers in order to achieve better performance. Organizations should overcome barriers such as the lack of trust and the sharing of sensitive information. This study offers insights from different perspectives that can help managers make informed decisions, therefore increasing the chances of success in those relationships. More specifically, from a managerial perspective, knowing the capabilities that contribute to organizational performance when establishing a relationship with a particular partner would be helpful to managers in maximizing the benefits realized from relationships.

This study has some limitations that open up interesting opportunities for future research. First, this study was carried out with a cross-sectional research design, in which all measurement items were collected at the same point of time. A longitudinal study could extend the current research by capturing the dynamics of the studied relationships. Second, this research employed only a quantitative method for data collection and analysis. Examining these relationships through qualitative methods, such as focus groups and interviews, may allow us to understand more thoroughly how these phenomena really take place in organizations. Third, there is currently constantly-changing research on BDA capabilities. So, the BDA capability dimensions used in this study should not be considered a universal model. Extending this research to include other BDA capabilities should idenitify other capabilities that might influence organizational performance.

Finally, this study only focused on a sample of Brazilian retail companies. Since big data is a global phenomenon, this study can be expanded by including a broader sample of firms outside Brazil. Because retailing is a context-driven discipline, retail characteristics vary across different regions according to the local economic, social, and institutional conditions (MIOTTO; PARENTE, 2015). It will be interesting to see if country-level differences affect the relationship between Inter-organizational collaboration, BDA capabilities and organizational performance.

We believe this study should stimulate organizations to go further on their collaboration relationships – advancing on the sharing of confidential information, equipment and people. By building the right relationships, organizations may be able to achieve competitive advantages and to innovate in a way they would not if they did not work this way. Hence, organizations may form big data collaborations to share investments and increase the number of datasets. In order to fully develop collaboration relationships, organizations need to implement governance mechanisms to manage risks, conflicts of interest, and establish some level of control and principles to govern such relationships.

This study opens up some opportunities for future work. This work has focused on medium and large-sized Brazilian retail companies. Since larger companies usually have more financial resources to make investments, it is expected that they are more capable of developing BDA capabilities. However, small companies could adopt low cost BDA resources, for example, using free software and technological solutions as well as developing relationships with other companies. In this way, studying how small companies develop their BDA capabilities and the effect the adoption of these capabilities have on their performance is of fundamental importance. Another important research agenda, since inter-organizational collaboration may involve sharing clients' private information and since privacy and confidentiality standards and laws exist, involves investigating the effects privacy demands have on collaboration and thus on organizational performance.

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Appendix A – Measurement items

Constructs	Items	Item description
BDA Capabilities – Technology	CAT1	Our organization adopts different tools to visualize data.
	CAT2	Our organization adopts cloud services to process and analyze data.
	CAT3	Our organization adopts free software to process and analyze data.
	CAT 4	Our organization uses integrated management systems (for example, CRM, ERP, among others)
	CAT5	Our organization has access to a great amount of unstructured data that can be analyzed (for example, social media data, internet websites data, videos, images, among others)
	CAT 6	Our organization integrates internal and external data from multiple sources to be able to analyze them (data originated from social media data, internet websites data, videos, images, among others sources)
BDA Capabilities – Human Talent	CAH1	Our organization provides training on data analysis to our employees (for example, through classroom or online training on data science and data analysis).
	CAH2	Our organization has employees with the necessary background to analyze data (for example, background in information technology and/or data Science or data analysis).
	CAH3	Our organization has employees with the necessary skills and experience in analyzing data to successfully carry out their work.
	CAH4	Our organization has trained employees in decision support systems (artificial intelligence, data warehousing, data mining).
	CAH5	Our organization has employees capable of interpreting problems and developing appropriate solutions.
BDA Capabilities - Managerial	CAM1	Our employees who are involved with data analysis comprehend and make decisions taking into account other functional managers' needs as well as our suppliers and clients.
	CAM2	Our employees who are involved with data analysis manage to analyze data together with other functional managers and/or with our suppliers and clients.
	CAM3	Our employees who are involved with data analysis are capable of anticipating other functional managers' needs, as well our suppliers and clients' needs.
	CAM4	Our employees who are involved with data analysis know how analyzed data can be used.
	CAM5	Our employees who are involved with data analysis are capable of comprehending and evaluating information extracted from data analysis.
BDA Capabilities – Data-driven Culture	CAC1	Our organization considers data are a valuable tangible asset.
	CAC2	Our organization bases its decision on data not on intuition.
	CAC3	Our organization accepts to reconsider its point of view when data analyzes contradicts our intuition.
	CAC4	Our organization continually assesses and improves its business rules/guidelines in response to data analysis.
	CAC5	Our organization orients its employees to make decisions based on data.
Inter-organizational	INS1	Our firm and supply chain partners exchange relevant information.

Collaboration – Information sharing	INS2	Our firm and supply chain partners exchange timely information.
	INS3	Our firm and supply chain partners exchange accurate information.
	INS4	Our firm and supply chain partners exchange complete information.
	INS5	Our firm and supply chain partners exchange confidential information
Inter-organizational Collaboration – Incentive Alignment	INA1	Our firm and supply chain partners co-develop systems to evaluate and publicize each other's performance.
	INA2	Our firm and supply chain partners share costs.
	INA3	Our firm and supply chain partners share benefits.
	INA4	Our firm and supply chain partners share any risks that can occur in the supply chain.
	INA5	Our firm and supply chain partners have incentives commensurate with our investment and risk.
Inter-organizational Collaboration – Resource sharing	RES1	Our firm and supply chain partners use cross-organizational teams frequently for process design and improvement.
	RES2	Our firm and supply chain partners dedicate personnel to manage the collaborative processes.
	RES3	Our firm and supply chain partners share technical support.
	RES4	Our firm and supply chain partners share equipment.
	RES5	Our firm and supply chain partners share financial and non-financial resources.
Organizational Performance - Financial performance	FIP1	Our organization improved customer retention during the last two years relative to our competitors.
	FIP2	Our organization improved sales growth during the last 2 years relative to our competitors.
	FIP3	Our organization improved profitability during the last 2 years relative to our competitors.
	FIP4	Our organization improved its market share during the last 3 years relative to our competitors.
Organizational Performance - Order process fulfillment performance	OPF1	Our organization is able to track orders with our suppliers and partners.
	OPF2	Our suppliers and partners' placing order process is easy.
	OPF3	Our supply chain partners offer us different shipping and handling charges and options.
	OPF4	Our supply chain providers and partners deliver our orders on time.
	OPF5	Our supply chain providers and partners deliver products without damage.
	OPF6	Our supply chain providers and partners delivers exactly the products our organization requests in the requested quantity.
	OPF7*	Our supply chain providers and partners do not usually return orders due to inconsistencies or damage.
Organizational Performance - Perception of Value	CPV1	Our products meet our clients' expectations.
	CPV2	Our organization provides good customer support.

	CPV3	Our client feels he/she is getting good value-added products and services for a reasonable price.
	CPV4	Our client feels that compared to other companies, it is wise to choose our company.
Technological Dynamism and Competitive Intensity	TDC1	Technology in our industry is rapidly changing.
	TDC2	Technological changes provide big opportunities in our industry.
	TDC3	A large number of new product ideas have been made possible through technological breakthroughs in our industry.
	TDC4	Our organization compete against highly qualified competitors in our industry.
	TDC5	Our organization is able to carry out any product and process improvement performed by our competitors.
	TDC6	Price competition is frequent in our industry.
	TDC7	There are many promotion wars in our industry.

*OPF7 was excluded from data analysis since its outer loading value was less than 0.40.

Appendix B – Crossloadings

	name	INC	INS	INA	RES	BDA	CAT	CAH	CAM	CAC	ORP	FIP	OPF	CPV
1	INS1	0.66591599	0.74490185	0.53014949	0.468734273	0.45964506	0.39610013	0.36474041	0.34954259	0.40857331	0.3099080	0.1425946142	0.33169249	0.22521100
2	INS2	0.57585846	0.73055398	0.48025554	0.322476664	0.23955312	0.23312661	0.21709198	0.21098465	0.12055002	0.1722934	0.0469283793	0.26746033	0.08744931
3	INS3	0.73943885	0.85665134	0.65533605	0.429917685	0.37189950	0.33816889	0.32580265	0.32584672	0.21985181	0.2326243	0.0086522849	0.29295853	0.22516353
4	INS4	0.66764397	0.79467666	0.55062676	0.395714675	0.39220200	0.37458665	0.33001975	0.31923375	0.25723394	0.3113890	0.1196562117	0.28261543	0.29295340
5	INS5	0.60143800	0.66391551	0.47057502	0.434318701	0.34756621	0.35498123	0.19062160	0.33283403	0.24286045	0.2359498	0.0392844298	0.22116835	0.26542507
6	INA1	0.67438129	0.57314755	0.69504065	0.461938330	0.46197791	0.46322593	0.36678225	0.36607746	0.32965311	0.3427369	0.2225697075	0.30357247	0.23863454
7	INA2	0.76897911	0.56214694	0.83683764	0.598322860	0.37709560	0.29088898	0.38173092	0.34344547	0.20379648	0.2760772	0.0374729582	0.27805252	0.27585655
8	INA3	0.68809540	0.55686304	0.80780522	0.411509808	0.35050914	0.36194493	0.23531872	0.30155771	0.23823694	0.2901583	0.1623188628	0.21074011	0.25906614
9	INA4	0.76228732	0.58238922	0.83567509	0.561383052	0.40664469	0.30313110	0.37947182	0.37558983	0.25254495	0.3166438	0.0722018369	0.27998308	0.33196212
10	INA5	0.68149385	0.51515335	0.74267614	0.511472865	0.31559775	0.31616083	0.30600141	0.24520298	0.15963576	0.2168495	0.0314103967	0.15861274	0.26401289
11	RES1	0.58684783	0.35102991	0.44784998	0.731311611	0.29253865	0.29505165	0.24312631	0.14925377	0.29592479	0.2485916	0.1079402827	0.23506074	0.20246194
12	RES2	0.63257762	0.43097523	0.48270634	0.751564598	0.24472672	0.20525498	0.24537684	0.15656797	0.20388828	0.1741315	0.0002715768	0.24680311	0.13509628
13	RES3	0.67967057	0.44466386	0.52351493	0.820087677	0.27811387	0.24377120	0.32997596	0.20751607	0.12199066	0.2505859	-0.0342341285	0.26194703	0.31317448
14	RES4	0.64172208	0.40407262	0.47281018	0.784498284	0.39161827	0.45847947	0.38268657	0.23252717	0.22830091	0.3675025	0.1261952206	0.36417651	0.32374987
15	RES5	0.72415772	0.47392754	0.60208598	0.813415144	0.38220586	0.42412360	0.37699814	0.25394398	0.18865529	0.3415667	0.0723668732	0.25129260	0.38650175
16	INS1	0.66619493	0.74502741	0.52983784	0.469587616	0.45830095	0.39441729	0.36499697	0.34834840	0.40630188	0.3095325	0.1385740316	0.33138024	0.22920201
17	INS2	0.57618519	0.72975963	0.48122582	0.323105497	0.23853328	0.22980478	0.21742432	0.21089790	0.11974598	0.1714054	0.0433075500	0.26975223	0.08720947
18	INS3	0.74261676	0.86149608	0.65692535	0.436296018	0.36799741	0.34087762	0.32766599	0.32009157	0.20946303	0.2128178	-0.0084973284	0.28178140	0.20414960
19	INS4	0.66909719	0.79682029	0.55312390	0.398014590	0.38862117	0.37486313	0.32698970	0.31467444	0.25213260	0.3027203	0.1113189728	0.27548847	0.28513577
20	INS5	0.60450749	0.66872787	0.47659709	0.435008359	0.33194776	0.34652605	0.17135259	0.31807433	0.23269959	0.2291154	0.0297750096	0.21331641	0.26840665
21	INA1	0.67755621	0.57930971	0.70085598	0.462907288	0.45291709	0.45208675	0.36079470	0.35788428	0.32555134	0.3292519	0.2061345576	0.30053024	0.22697160
22	INA2	0.76901347	0.56274531	0.83674557	0.598232807	0.37681090	0.29195233	0.38093282	0.34300599	0.20298051	0.2758273	0.0369703817	0.27790802	0.27580315
23	INA3	0.68821649	0.55824487	0.80849247	0.410261908	0.34919485	0.36070910	0.23498456	0.30011374	0.23724698	0.2902262	0.1629834780	0.21213781	0.25768935
24	INA4	0.76234297	0.58282752	0.83623953	0.560766534	0.40620003	0.30426464	0.37862771	0.37485320	0.25133040	0.3165050	0.0717932127	0.27964757	0.33207161
25	INA5	0.68340159	0.52077729	0.74538654	0.511230542	0.31078119	0.31047929	0.30177167	0.23927020	0.16069565	0.2071488	0.0236074180	0.15482429	0.25424314
26	RES1	0.59538832	0.36043945	0.45801683	0.744225311	0.26102652	0.25807543	0.22057769	0.12947703	0.26624267	0.2179024	0.0684191298	0.21860293	0.18396188

27	RES2	0.63549051	0.43462358	0.48288788	0.759994152	0.23446390	0.20072644	0.23915954	0.14078688	0.19681210	0.1625826	-0.0148327338	0.24578335	0.12200537
28	RES3	0.68029973	0.44668920	0.52065622	0.822916464	0.27860816	0.24351876	0.33057376	0.20828418	0.12282006	0.2459531	-0.0389783095	0.25926789	0.31076114
29	RES4	0.64183452	0.40401776	0.47296048	0.784660465	0.39093890	0.45619693	0.38301491	0.23302720	0.22727778	0.3675002	0.1257843410	0.36437155	0.32427417
30	RES5	0.72450307	0.47471036	0.60372978	0.812454056	0.38267499	0.42271224	0.37675446	0.25496458	0.19009448	0.3383867	0.0663586093	0.25059527	0.38483711
31	CAT1	0.46613805	0.44938381	0.38659329	0.363462344	0.63209601	0.74204934	0.41584787	0.41383880	0.54220749	0.4373252	0.2836311458	0.29836761	0.38953957
32	CAT2	0.52170172	0.43536888	0.48951430	0.445929175	0.48144467	0.55353874	0.42039387	0.36004058	0.26324981	0.2385002	0.0278793465	0.20110428	0.26202136
33	CAT3	0.20484448	0.14673586	0.20766254	0.161515054	0.45911243	0.54435614	0.29726997	0.31053761	0.40216187	0.2635794	0.1660049491	0.23202875	0.18472544
34	CAT4	0.16448205	0.17281309	0.13878876	0.091914888	0.32256661	0.48330249	0.13645081	0.22247914	0.24100736	0.1530632	0.1469860649	0.02093866	0.16724478
35	CAT5	0.37403866	0.32276174	0.30830521	0.319745723	0.62515909	0.81150745	0.43773633	0.40486905	0.44737652	0.4920605	0.3268536173	0.31075709	0.47065955
36	CAT6	0.24444462	0.21687193	0.18703610	0.195236588	0.59358753	0.74093427	0.47046937	0.41686108	0.39332894	0.4087518	0.4230917849	0.21506426	0.29224588
37	CAH1	0.35497833	0.26842705	0.29875687	0.330790970	0.72807037	0.59004991	0.78249691	0.55899351	0.51751260	0.4132036	0.2991369223	0.29420530	0.32384600
38	CAH2	0.32449258	0.21928781	0.34972878	0.268828215	0.42985961	0.27581670	0.65671244	0.36808873	0.14174293	0.1757563	-0.0166446511	0.23897192	0.16745698
39	CAH3	0.26981131	0.22262507	0.26703784	0.204690892	0.46753181	0.20268407	0.69910967	0.45358393	0.21367680	0.1407362	0.0115422645	0.15771624	0.14803303
40	CAH4	0.45021130	0.37912674	0.37535890	0.394292964	0.65792760	0.54212219	0.77240781	0.50841418	0.39063889	0.3350047	0.1613610855	0.31761665	0.27305920
41	CAH5	0.29283644	0.25596442	0.27149918	0.229550244	0.57267599	0.33695541	0.68987705	0.48356591	0.41271193	0.2553657	0.1064621869	0.21067360	0.24854839
42	CAM1	0.38875139	0.36373574	0.34971763	0.278405398	0.71773790	0.45800992	0.51808683	0.80612104	0.54592822	0.3105227	0.1923259929	0.20131077	0.27718983
43	CAM2	0.45074770	0.39219955	0.41750591	0.348187606	0.72544100	0.47348334	0.57649076	0.80799872	0.48165681	0.3942950	0.1963857337	0.29119609	0.37947111
44	CAM3	0.41033077	0.35443194	0.44676846	0.238930192	0.75163504	0.51312548	0.59964267	0.83261825	0.50146482	0.3816589	0.2559170652	0.28615106	0.29799529
45	CAM4	0.25523746	0.28819243	0.27228795	0.073651147	0.71264525	0.41781744	0.55279876	0.83325665	0.53097172	0.3923398	0.3845569851	0.29610613	0.23468523
46	CAM5	0.22611515	0.25363215	0.21393462	0.100402170	0.69716640	0.41242451	0.50653452	0.82784706	0.53782267	0.3061809	0.3163902320	0.24025245	0.15922453
47	CAC1	0.36130369	0.27852251	0.33439388	0.313459150	0.59498533	0.36578230	0.41195507	0.49021170	0.67840453	0.3455706	0.2155768215	0.16305130	0.37126453
48	CAC2	0.32803718	0.30527610	0.24700173	0.283722016	0.70169848	0.56822647	0.45678065	0.49906395	0.81822704	0.4582160	0.3659279745	0.21044909	0.43331467
49	CAC3	0.14111929	0.13579868	0.10387024	0.115883874	0.54822611	0.38239799	0.30387019	0.42163125	0.73205951	0.3636490	0.3863866227	0.16589749	0.26419177
50	CAC4	0.25021353	0.25962164	0.20606397	0.162712722	0.60987084	0.43430023	0.32753815	0.47282636	0.79536971	0.3623423	0.3718471885	0.15614696	0.27654708
51	CAC5	0.28055783	0.27154214	0.29166317	0.143765819	0.67842067	0.52430828	0.41003607	0.53987954	0.77923758	0.4067339	0.3444202481	0.22176918	0.33219948
52	CAT1	0.46151240	0.44550761	0.38307673	0.358600032	0.63245292	0.74345825	0.41193101	0.41597569	0.54357052	0.4392560	0.2859156683	0.29893328	0.39153998
53	CAT2	0.49697028	0.41397440	0.46470464	0.426390494	0.48355122	0.56021659	0.42092477	0.35822403	0.26928067	0.2440995	0.0474991914	0.20264675	0.25708175
54	CAT3	0.20477492	0.14609948	0.20763786	0.161965093	0.45914375	0.54542502	0.29708765	0.31007295	0.40202721	0.2632238	0.1661652631	0.23084642	0.18457715
55	CAT4	0.16150780	0.16861512	0.13423069	0.093839610	0.32378474	0.48348960	0.13790373	0.22543478	0.24200348	0.1451754	0.1433533357	0.02090686	0.15544852

56	CAT5	0.37099651	0.31895387	0.30632732	0.317206129	0.62544837	0.81191313	0.43920838	0.40505627	0.44662305	0.4924184	0.3291442751	0.30888137	0.47169698
57	CAT6	0.24332638	0.21671925	0.18753948	0.192482184	0.59444097	0.74125957	0.46842269	0.42065046	0.39382846	0.4034628	0.4190365764	0.21300862	0.28438097
58	CAH1	0.35546403	0.26886240	0.29886253	0.331830523	0.72814920	0.58917585	0.78307064	0.55933630	0.51787108	0.4119686	0.2984742057	0.29296468	0.32306891
59	CAH2	0.32230427	0.21885270	0.34673304	0.266599408	0.43011155	0.27226829	0.66034586	0.36941532	0.14247231	0.1746655	-0.0150980470	0.23981895	0.16435335
60	CAH3	0.25135750	0.20753410	0.25210592	0.185203236	0.46938087	0.20159968	0.70065266	0.45730573	0.21924317	0.1416446	0.0218535426	0.15202395	0.14750599
61	CAH4	0.44644153	0.37621349	0.37115847	0.391069497	0.65858807	0.54231115	0.77403791	0.51050994	0.38906067	0.3334304	0.1620789484	0.31474238	0.27060550
62	CAH5	0.28954250	0.25486245	0.26694191	0.226853142	0.57373213	0.33871748	0.68513874	0.48549871	0.41721356	0.2506518	0.1084776484	0.20118937	0.24391407
63	CAM1	0.37962173	0.35432887	0.34420134	0.270572724	0.72051610	0.45066856	0.51890030	0.81706979	0.55193969	0.2975467	0.1893743318	0.19283302	0.25997481
64	CAM2	0.44142032	0.38646781	0.40969994	0.337132564	0.72736781	0.47363682	0.57681441	0.80996486	0.48770432	0.3866952	0.1869017765	0.28921501	0.37510127
65	CAM3	0.41129346	0.35474425	0.44815801	0.240015700	0.75186002	0.51541305	0.59705728	0.83184320	0.50300452	0.3792604	0.2525968135	0.28393219	0.29662137
66	CAM4	0.25776978	0.29105018	0.27340032	0.077278376	0.71324517	0.41668312	0.55323660	0.83399546	0.53390400	0.3843245	0.3769789673	0.29130248	0.22825302
67	CAM5	0.22300030	0.25227673	0.21240473	0.094962729	0.69792135	0.41035185	0.50868080	0.82988300	0.54001373	0.3019482	0.3140647359	0.24107355	0.15171132
68	CAC1	0.35785231	0.27586226	0.32896808	0.312631216	0.59529680	0.36446622	0.41170717	0.48849567	0.68413984	0.3446275	0.2174261256	0.16207911	0.36864854
69	CAC2	0.31833033	0.30555706	0.24103360	0.264121351	0.70426031	0.56678005	0.45373296	0.50334100	0.83124502	0.4431710	0.3670656593	0.19911744	0.41176068
70	CAC3	0.13373115	0.13192425	0.09605202	0.107663066	0.54887056	0.38087414	0.30171133	0.42192582	0.73818269	0.3655489	0.3915585695	0.16712548	0.26343189
71	CAC4	0.23793027	0.24918402	0.19040145	0.156740771	0.61113329	0.43276618	0.32710433	0.47467463	0.80191373	0.3627417	0.3730239398	0.15671664	0.27853353
72	CAC5	0.26413653	0.26179097	0.27679125	0.124912864	0.68031245	0.52386635	0.40431731	0.54501857	0.78883921	0.4063973	0.3539121723	0.21658551	0.32990639
73	FIP1	0.10371610	0.04843057	0.11115565	0.069627511	0.32278997	0.25267300	0.19332934	0.26041532	0.37243345	0.6188863	0.8118526701	0.25618081	0.38190849
74	FIP2	0.14216988	0.12059234	0.13677133	0.074723132	0.38612790	0.34648545	0.16264177	0.33547753	0.42184375	0.7017414	0.8671860764	0.29127870	0.44836109
75	FIP3	0.16991863	0.11018585	0.17891881	0.121387799	0.40364695	0.41350962	0.22681940	0.30670365	0.38927338	0.6833177	0.7996467392	0.34387558	0.39779925
76	FIP4	0.03041287	0.03967445	0.04284286	-0.041050283	0.27821049	0.27972714	0.08789473	0.20394989	0.35716141	0.6497529	0.8807905320	0.25921518	0.38051837
77	OPF1	0.29430797	0.26206143	0.30382682	0.185725367	0.20654266	0.26250850	0.24885735	0.14407784	0.04483729	0.3790155	0.1955109798	0.56505669	0.14941260
78	OPF2	0.35318325	0.28695496	0.23427204	0.388472642	0.38738649	0.35444289	0.30959513	0.29094374	0.32499974	0.5812881	0.2775912292	0.73647863	0.35298436
79	OPF3	0.09500407	0.11961761	0.13277437	-0.023809914	0.19194912	0.17809488	0.11374052	0.20267503	0.15176760	0.4549108	0.3748882618	0.58023843	0.20425716
80	OPF4	0.06785787	0.12575419	0.03533107	0.019974536	0.04860791	0.09885995	0.07038036	0.02896609	-0.02459590	0.2998502	0.1559600238	0.52005053	0.11323851
81	OPF5	0.45024979	0.33554989	0.35458358	0.484785117	0.30973819	0.21553568	0.34227403	0.27340903	0.15082464	0.4023283	-0.0084268316	0.50684937	0.41195371
82	OPF6	0.22920918	0.20592649	0.15795908	0.226197958	0.17226219	0.12499867	0.17638246	0.15403947	0.09912066	0.4128614	0.1282043387	0.64580388	0.24813139
83	CPV1	0.24374730	0.22498200	0.17851830	0.196894685	0.44995734	0.48727915	0.26912548	0.33462599	0.39807921	0.6164437	0.4245781135	0.33329773	0.66279640
84	CPV2	0.42436454	0.29881953	0.35864764	0.443428012	0.30640560	0.33088452	0.25748427	0.11478835	0.30893337	0.5243864	0.1472167158	0.33029980	0.69885132

85	CPV3	0.23737994	0.12353246	0.27226207	0.200995885	0.28085074	0.22734211	0.19414535	0.22059647	0.26701336	0.5994731	0.3415124410	0.28443292	0.77452220
86	CPV4	0.29677374	0.23545600	0.27609727	0.241015022	0.39416843	0.37041728	0.28720024	0.28984928	0.34172809	0.6723750	0.4129574987	0.29956752	0.82414270
87	FIP1	0.09138661	0.03530123	0.09590858	0.065789076	0.31353177	0.24686191	0.18732917	0.25567072	0.35750975	0.6221511	0.8166354821	0.26231046	0.38273584
88	FIP2	0.13283559	0.11409143	0.12756716	0.064879540	0.37819444	0.34188056	0.15651557	0.32771012	0.41553448	0.7034882	0.8784837139	0.29503854	0.44526704
89	FIP3	0.14040524	0.08757382	0.15877803	0.085253508	0.38444131	0.38969013	0.20769055	0.29752868	0.37898617	0.6896643	0.8250167297	0.34691532	0.39864417
90	FIP4	0.02561963	0.03468891	0.03630260	-0.042463413	0.27384041	0.28154045	0.08398197	0.19946314	0.34891642	0.6521049	0.8829734942	0.26346135	0.38024243
91	OPF1	0.25833211	0.24038302	0.26618480	0.148716698	0.18031337	0.24440886	0.22367103	0.11197158	0.03868785	0.3859976	0.2181236473	0.57632636	0.15220803
92	OPF2	0.34187152	0.28423262	0.22992378	0.365703323	0.37705413	0.34485262	0.29222344	0.28173976	0.32772084	0.5835194	0.2865455301	0.74190926	0.34894209
93	OPF3	0.07518718	0.11244940	0.10641459	-0.041832586	0.18241752	0.16149217	0.10430343	0.20901730	0.13751035	0.4586204	0.3921229243	0.58246804	0.20243913
94	OPF4	0.05545285	0.12526196	0.02065156	0.002619743	0.04536415	0.08914565	0.06280927	0.02965084	- 0.02010516	0.3014660	0.1559206475	0.53209306	0.11202768
95	OPF5	0.45114364	0.33378747	0.35208232	0.490874262	0.30330752	0.21146055	0.33887474	0.26895076	0.14157946	0.4030704	-0.0018332761	0.50499652	0.40967386
96	OPF6	0.19678367	0.18785457	0.12664457	0.191523015	0.17833156	0.12580454	0.16770374	0.16768683	0.11188725	0.4166880	0.1398330738	0.64731836	0.24826991
97	CPV1	0.23708023	0.21825318	0.16780849	0.196491129	0.44283399	0.47688353	0.26790585	0.32884485	0.39347807	0.6182309	0.4358614866	0.33141556	0.66107141
98	CPV2	0.41762445	0.29416165	0.35106825	0.438520937	0.30164586	0.32765938	0.25429899	0.10666503	0.30992086	0.5255305	0.1506301460	0.33431915	0.69876534
99	CPV3	0.22511505	0.11717850	0.25544141	0.191272732	0.27022968	0.21350037	0.18707315	0.21774026	0.25571835	0.6020020	0.3562344766	0.29020840	0.76884742
100	CPV4	0.27945907	0.22262466	0.26138691	0.223345146	0.37387660	0.35205810	0.27548061	0.27344549	0.32289933	0.6769753	0.4262571952	0.30341490	0.82946186