A qualitative analysis to investigate the enablers of big data analytics that impacts sustainable supply chain

Lineth Arelys Rodriguez Pellière

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Par
« Lineth RODRÍGUEZ »

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Rapporteurs avant soutenance :

GRABOT Bernard PU, ENIT
ALVAREZ Humberto PU, Univ. Tecnológica de Panamá

Composition du Jury :

Président : DEPINCE Philippe PU, Polytech Nantes

Examinateurs : RAUFFET Philippe MC, ENSIBS

Dir. de thèse : DA CUNHA Catherine MC, Ecole Centrale de Nantes
Co-dir. de thèse : GIANNAKIS Mihalis PU, Audencia Business School

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Abstract

Scholars and practitioners have already shown that Big Data and Predictive Analytics (also known in the literature as BDPA) can play a pivotal role in transforming and improving the functions of sustainable supply chain analytics (SSCA). However, there is limited knowledge about how to make better use of BDPA to increase the social, environmental, and financial performance simultaneously.

Therefore, with the knowledge coming from literature around SSCA, it seems that companies still struggle to implement SSCA practices. Researchers agree that there is still a need to understand the techniques, tools, and enablers of the basics SSCA for its adoption; this is even more important to integrate BDPA as a strategic asset across business activities. Hence, this study investigates, for instance, what are the enablers of SSCA and what are the tools and techniques of BDPA that enable the triple bottom line (3BL) of sustainability performances through SSCA.

The thesis adopted moderate constructionism from an understanding of how the enablers of big data impact sustainable supply chain analytics applications and performances. The thesis also adopted a questionnaire and a case study as a research strategy in order to capture the different perceptions of the people and the company on big data applications on sustainable supply chain analytics.

The thesis revealed a better insight into the factors that can affect the adoption of big data on sustainable supply chain analytics. Besides, this research was capable to find the factors depending on the variable loadings that impact on the adoption of BDPA for SSCA, tools, and techniques that enable decision making through SSCA, and the coefficient of each factor for facilitating or delaying sustainability adoption that was not investigated before. The findings of the thesis suggest that the current tools that companies are using by themselves cannot analyze data. The companies need more appropriate tools for data analysis.

Keywords: sustainability, sustainable supply chain, big data and predictive analytics, enablers

Résumé en français

Les académiques et les professionnels ont déjà montré que le Big Data et l'analyse prédictive, également connus dans la littérature sous le nom de BDPA, peuvent jouer un rôle fondamental dans la transformation et l'amélioration des fonctions de l'analyse de la chaîne d'approvisionnement durable (SSCA). Cependant, les connaissances sur la meilleure manière d'utiliser la BDPA pour augmenter simultanément les performances sociales, environnementale et financière.

Par conséquent, avec les connaissances tirées de la littérature sur la SSCA, il semble que les entreprises peinent encore à mettre en œuvre les pratiques de la SSCA. Les chercheurs conviennent qu'il est encore nécessaire de comprendre les techniques, outils et facteurs des concepts de base de la SSCA pour adoption. C'est encore plus important d'intégrer BDPA en tant qu'atout stratégique dans les activités commerciales.

Par conséquent, cette étude examine, par exemple, quels sont les facteurs de SSCA et quels sont les outils et techniques de BDPA qui permettent de mettre en évidence le 3BL (pour ses abréviations en anglais : "triple bottom line") des rendements de durabilité (environnementale, sociale et financière) via SCA.

La thèse a adopté un constructionnisme modéré, car elle comprend l'impact des facteurs Big Data sur les applications et les indicateurs de performance de la chaîne logistique analytique et durable. La thèse a également adopté un questionnaire et une étude de cas en tant que stratégie de recherche permettant de saisir les différentes perceptions des personnes et des entreprises dans l'application des mégadonnées sur la chaîne d'approvisionnement analytique et durable.

La thèse a révélé une meilleure vision des facteurs pouvant influencer l'adoption du Big Data dans la chaîne d'approvisionnement analytique et durable. Cette recherche a permis de déterminer les facteurs en fonction des variables ayant une incidence sur l'adoption de BDPA pour SSCA, des outils et techniques permettant la prise de décision via SSCA et du coefficient de chaque facteur pour faciliter ou retarder l'adoption de la durabilité. Il n'a pas été étudié avant. Les résultats de la thèse suggèrent que les outils actuels utilisés par les entreprises ne peuvent pas analyser de grandes quantités de données par eux-mêmes. Les entreprises ont besoin d'outils plus appropriés pour effectuer ce travail

Mots-clés : Durabilité, Analyse de la Chaîne d'Approvisionnement, Big Data et Analyse Prédictive, Facteurs

Resumen en español

Los académicos y profesionales ya han demostrado que el Big Data y el Análisis Predictivo también conocidos en la literatura como BDPA pueden desempeñar un papel fundamental en la transformación y mejora de las funciones del análisis de la cadena de suministro sostenible (SSCA). Sin embargo, existe un conocimiento limitado sobre cómo se puede aprovechar mejor el BDPA para aumentar el desempeño social, ambiental y financiero de manera simultánea.

Por lo tanto, con el conocimiento proveniente de la literatura en torno a SSCA, parece que las compañías aún luchan por implementar las prácticas de SSCA. Los investigadores están de acuerdo en que aún es necesario comprender las técnicas, herramientas y factores de los conceptos básicos de SSCA para su adopción; esto es aún más importante para integrar BDPA como un activo estratégico en las actividades comerciales.

Por lo tanto, este estudio investiga, por ejemplo, cuáles son los factores de SSCA y cuáles son las herramientas y técnicas de BDPA que permiten resaltar el 3BL (por sus siglas en inglés: “triple bottom line”) de los rendimientos de sostenibilidad (ambiental, social y financiero) a través de SCA.

La tesis adoptó un construccionismo moderado, ya que comprende cómo los factores de Big Data impactan en las aplicaciones y en los indicadores de rendimientos de la cadena de suministro analítica y sostenible. La tesis también adoptó un cuestionario y un caso de estudio como estrategia de investigación para capturar las diferentes percepciones de las personas y las compañías en la aplicación de Big data sobre la cadena de suministro analítica y sostenible.

La tesis reveló una mejor visión de los factores que pueden afectar la adopción de Big Data en la cadena de suministro analítica y sostenible. Esta investigación fue capaz de encontrar los factores dependiendo de las variables que impactan la adopción de BDPA para SSCA, las herramientas y técnicas que permiten la toma de decisiones a través de SSCA y el coeficiente de cada factor para facilitar o retrasar la adopción de sostenibilidad que no ha sido investigado con anterioridad. Los hallazgos de la tesis sugieren que las herramientas actuales utilizadas por las empresas no pueden analizar grandes cantidades de datos por sí mismas. Las empresas necesitan herramientas más adecuadas para poder realizar dicho trabajo.

Palabras clave: Sostenibilidad, Análisis de la Cadena de Suministro, Big Data y Análisis Predictivo, Factores

Thesis Summary

Chapter One: Introduction

Introduction

Big Data and Predictive Analytics (BDPA) have become crucial for managing supply chain functions where intensive data processes can be improved vastly through their effective use. Big Data and Predictive Analytics (BDPA) have emerged as both a strategic and operational tool that may bring fundamental changes to the Supply Chain (SC) (Wu et al. 2015; Waller and Fawcett 2013; Song et al. 2017; Zhao et al. 2017).

As an asset for decision-making, BDPA can play a pivotal role in transforming and improving the functions of Supply Chain. Additionally, practitioners and scholars are wondering how BDPA impact the three sustainability aspects (environmental, economic, and social) in the supply chain.

Chapter Two: Literature Review

Sustainable Supply Chain Pillars: The 3BL

Economic

The main objective of companies is to make money and generate profits. Even for non-profit organizations, money is essential for them to continue operating. The economic performance represents the ability of a company to offer returns to its shareholders. (Carter & Rogers 2008) argue that developing social and environmental knowledge and resources is difficult to imitate.

Social

Although the focus on the environment has dominated the studies on sustainability in SCM (Ashby et al. 2012; Lee et al. 2014; Vachon & Klassen 2006a), there is an increasing trend in considering the social dimension of sustainability. (Awaysheh & Klassen 2010) identify social practices as those management practices that affect the development of human beings and the protection of people. The improvement in the social pillar represents an opportunity for companies to improve their relationships with communities, shareholders, employees, and customers (Carter & Easton 2011; Carter & Jennings 2002).

Environmental

The environmental pillar in sustainability has received a lot of attention in the literature (Klassen & Vereecke 2012) where the general aim of this pillar is to identify the interaction of companies with the natural environment. The concern over environmental issues, such as resource depletion, pollution, climate change, ozone layer depletion, and waste management, has escalated the governmental and business attentions toward protecting the environment

(Góncz et al. 2007). The environmental pillar in sustainability means that companies should consider their activities' impact on the environment and include these considerations in their daily activities and operations.

Big Data and Predictive Analytics

As part of this analysis, this study explores emerging technologies that are driving major innovation and represent potential changes in the sustainable supply chain analytics design. This technology is big data and predictive analytics (BDPA). There is no clear consensus on different terminologies related to big data in the literature.

Based on the nature of data, Big Data (BD) was characterized mainly by three dimensions (3V's) 'Volume,' 'Velocity', and 'Variety' (IBM 2015; Brown et al. 2011; Sonka 2014; Gunasekaran et al. 2016). But, apart from the 3V's Big Data can also be characterized by another two dimensions 'Veracity' and 'Value'.

The value of using Big Data and Predictive Analytics (BDPA)

According to McKinsey and Company, big data and predictive analytics (BDPA) would be an opportunity to knuckle down some challenges that the industry is facing. For example, improve customer experience, making sense of large amounts of unused business data, improve inaccurate or misleading revenue forecasts and models, focus on micro-decisions, etc. (Court 2015). This consultancy firm found that collecting, storing, and mining BDPA for insights can create significant value for the world economy, enhancing the productivity and competitiveness of companies and the public sector and creating a substantial economic surplus for consumers (Manyika et al. 2013; Brown et al. 2011). Due to the perceived benefits of BDPA, organizations are highly motivated to develop their technical and organizational capabilities to extract value from data. The core aspects of generating value depend on the organization's ability to capture, store, and analyze a large volume of complex data generated in real or near real-time with the support of advanced analytics (Yesudas et al. 2014). Further, recent studies show that supply chains are gathering huge amounts of data, but companies and practitioners are facing extreme difficulties in understanding the required capabilities to transform data into value (Lisa & Toby 2017; Rogers Dale 2017; Richey et al. 2016).

Sustainable Supply Chain Management (SSCM)

Companies in the manufacturing and service industries have witnessed dramatic changes in terms of how companies conduct their activities and operations. Internationalization of companies and global sourcing, rapid technology development, and shorter product life cycle (Hutchins & Sutherland 2008; Vermeulen & Seuring 2009) are some of the most influencing factors that force companies to restructure their organizations and supply chains. Under these operating conditions, companies' supply chains reach increasingly several geographical areas, and this poses risks to companies on how to take care of their activities' impact on sustainability. Although supply chains are effectively structured to achieve economic and competitive advantages, they are often sources of sustainability risk. For example, sourcing from low-cost countries can achieve economic benefits, but the transfer of goods to Europe

and the USA may increase CO2 emission and energy consumption (Abbasi & Nilsson 2012). In addition, companies must avoid social and ethical issues in such regions to protect their brand image and reputation. Therefore, the scope of companies' sustainability implementation has been extended to include the upstream and downstream activities in their supply chains. This has implications that companies are responsible for their suppliers' activities that impact on sustainability as well as the product through its life cycle till its final disposal (Ashby et al. 2012; Awaysheh & Klassen 2010; Rao & Holt 2005; Seuring & Müller 2008). As mentioned by (Carter & Easton 2011) "the broad concept of sustainability and the key interfaces that sustainability has with supply chain management suggest strongly that sustainability is instead a license to do business in the twenty-first century. And supply chain management is an integral component of this license."

Sustainable Supply Chain Analytics (SSCA)

Sustainable Supply Chain Analytics (SSCA) is described as the use of business analytics in the collection, analysis, and circulation of sustainability-related data. The objective is to line the opportune information that can be used for effective and efficient decision-making on sustainability issues (Deloitte 2013). The literature has highly pointed the need by organizations to manage and collaborate closely with suppliers and customers on sustainability concerns (Leppelt et al. 2013) to accomplish better control of risks and organizational sustainability (Foerstl et al. 2010; Paulraj 2011). For this purpose, Supply Chain Analytics (SCA) can gather and analyze sustainability-related data efficiently and effectively, thus supporting a variety of informational needs that include forecasting, analysis, and evaluation of economic, environmental, and social issues. Organizations need to develop and acquire capabilities to enable sustainable SCA. Therefore, we do recognize that sustainable SCA requires broader thinking and alignment between strategic goals and big data analytics as well as supporting organizational culture (Richardson 2011; Ransbotham 2017; Wang et al. 2016). Scholars have enhanced the relationship between strategic goals, culture, transparency, and risk management as the building blocks of sustainable SCA (Ageron et al. 2013; Mello & Stank 2005; Gunasekaran & Spalanzani 2012). To enable this relationship, BDPA and SSCA come to the foreground to secure the collection, cleansing, analysis, and distribution of information seamlessly across functions and processes (IBM 2018). It is important that leaders understand the role of SSCA to build the format needed for taking strategic decisions related to sustainability. This will enable leaders to acquire the appropriate analytical capabilities as well as the appropriate resources needed on adopting SSCA to create organizational value through the fulfillment of the organizational goals (Bertels 2010; Deloitte 2012). Top and senior management commitment is a priority for those organizations and supply chains that are embracing sustainable practices (Foerstl et al. 2015; Gattiker & Carter 2010).

Factors and Enablers for implementing sustainable supply chain analytics.

Introduction

Sustainable supply chain analytics (SSCA) has become a salient issue in recent research. SSCA combines the concepts of supply chain management and sustainability (Turker & Altuntas 2014) and entails all activities of companies to increase the sustainability of their supply chains (Pagell & Wu 2009) with the characteristics of Big Data Analytics. As mentioned before in the section "Sustainable SCA", researchers have already identified several drivers and barriers to a successful implementation of SSCA (Diabat et al. 2014; Oelze 2017). However, there is no research completed that seeks to identify the influence degree of each factor for facilitating/delaying sustainability adoption (Wang et al. 2016; Firouzeh et al. 2017). This research aims to follow the advice of other scholars to estimate the impact factor of enablers/disruptions using big data and predictive analytics on SSCA.

Enablers of Sustainable SCA

The enablers of SSCA (Walker et al. 2008; Lin et al. 2010) are the factors that motivate the adoption of sustainable supply chain analytics. These enablers are described for any innovation explained before as well as for SSCA. That is why they have been included in the conceptual framework. The present study focuses on analyzing the enablers for SSCA adoption from environmental, economic, and social perspectives. This research sought a fit for sustainable adoption of the traditional supply chain by using the terms "sustainable supply chain management; enablers for green supply chain and supply chain innovation." The identified enablers are shown in Table 3 and Table 4 respectively. I must point out that in the original papers were 25 enablers and they were focused on the green supply chain. On the other hand, for this study, it has been used eleven significant (11) enablers. These enablers were divided into two groups external/internal, as you will see below.

Internal Enablers

A requisite for fruitful implementation of SSCA standards is the compliance of the company's employees. Scholars frequently are mentioning the commitment of the top management, but also their involvement and specific support as being beneficial (Oelze 2017). In the same manner, an overall supportive culture for sustainability, the existence of an environmental mission, and the history of an organization are acknowledged enablers for SSCA. These include the involvement of employees.

Additionally, state of the art brought us strategic aspects. Thus, the existence of a sustainability strategy for supply chain analytics and its alignment with the overall corporate strategy has been identified as crucial (Dey et al. 2011; Hervani et al. 2005). The basic strategic planning of the implementation of SSC policies has already been recognized as conducive to their successful implementation (Klimley 2007). Further, strategic supplier collaboration has been defined as the "collaborative paradigm" that is essential to achieve a competitive advantage through sustainable supply chain analytics (Firouzeh et al. 2017; Mani et al. 2017; Wang et al. 2016).

Furthermore, previous research enhances the resources and expertise of companies in the context of enablers for SSC. More specifically, the availability of resources and the overall

size of a company constitute enablers for SSC since they determine the possible sustainability effort of a firm (Alvarez et al. 2010). Besides, the existence or development of capabilities related to sustainability and general supply chain are highlighted in the academic literature (Large & Gimenez Thomsen 2011). This relates to the training of people within the purchasing department (Andersen & Skjoett-Larsen 2009). Moreover, prior studies suggest evidence for well-performing operational metrics as an enabler for SSC (Sikdar 2003; Clift 2003). In Table 9, you will see the internal enablers related to the top management and the methodology used by each author to reach their studies.

External Enablers

External enablers are firmly related to the global context in which a firm works. On this point, the national culture of a supplier can constitute an enabling factor for SSCA (Ciliberti et al. 2010a). Moreover, a technological and logistical integration of supply chain members and information sharing are conducive to successful implementation (Vachon & Klassen 2006a; Zsidisin & Hendrick 1998). According to this, it can also reduce the need for audits through an enhanced understanding of suppliers' processes (Barratt 2004). However, SSCA is only supported when the relationships between the focal firm and its supply chain members are characterized by trust and transparency (Oelze et al. 2016; Ciliberti et al. 2010b). In this respect, long-term collaborative structures within but also outside the supply chain support SSCA. This applies in particular to collaboration within a sector with NGOs or with competitors (Pagell & Wu 2009; Oelze et al. 2016; Vachon & Klassen 2006b). In this chapter, you will see the external enablers related to the top management and the methodology used by other authors.

Absorptive Capacity

The relevance of dynamic capabilities specifically absorptive capacity as a moderator factor and pre-requisite for innovation implementation was addressed in several research works (Kabir and Carayannis 2013; Wang et al. 2015; Wamba et al. 2017; Arunachalam et al. 2017). Studies linking DCs with SSCM practices and DCs influences in creating innovation (Beske 2012; Čiutienė & Thattakath 2014). However, many large firms still fail to implement BDPA due to the lack of the right capabilities to support innovation (Assink 2006; Čiutienė & Thattakath 2014).

Conclusions

This chapter discussed the literature review, identified research gaps, interaction approach, and the main concepts that are adopted for studying how the enablers of big data impact on sustainable supply chain analytics. The next chapter presents and discusses the research methodology, research questions, and conceptual framework that are applied in this thesis.

Chapter Three: Research Methodology

Research Approach

The research subject of "Investigating the enablers of Big Data on Sustainable Supply Chain Analytics" is complex and dynamic as it is concerned with the interaction and change of internal and external processes that take place within an inter-organizational context. A quantitative and qualitative approach based on questionnaires and case studies are more appropriate to this thesis due to the nature of research gaps and questions. The case study approach has enabled collecting data from the employees of "The Company A" on how sustainable supply chain analytics using big data strategies are implemented. On the other hand, the questionnaires target the supply chain professionals that are able to identify the currents problems of the supply chain field in their firms.

The research presented in this manuscript was conducted in two phases. The first phase was the development to understand the enablers. A questionnaire was carried out and it was developed on Google forms based on the literature review and inspired by (Creswell 2003; Fallis 2005; Watson et al. 2004; Wacker 1998) (bit.ly/enablers_ssc_questionnaire). Since on-site visits were not possible, the questionnaire was sent directly via email and messages (e.g. WhatsApp and Facebook Messenger), contacting around 50 people and posted – both as free and sponsored content - through social networks such as LinkedIn and Facebook. The audience of the social network groups was reported to be around 10k people; however, the number of people that effectively reached was not measured because many external variables were out of control. The aim of this study is to get at least 35 valid answers to conduct the statistical analysis. Target participants are senior executives from different countries who are able to identify the problem of the supply chain to which their firms belong and who are responsible for SCM and thus, they were qualified to provide a valid response to this research. All of them were asked to complete and return the questionnaire form with scales measuring the enablers of implementation of sustainable supply chain analytics. Then, the answers to this questionnaire will be analyzed with Exploratory Factor Analysis.

The second phase consisted of conducting a case study with a large Panamanian Company and its employees in which it was denominated "The Company A" due to a nondisclosure agreement between the author and the company. The analysis process was based on the analysis of a huge quantity of data (e.g., massive items) that the company provided; the chapter 4 will focus on data analysis usefulness with a big data analytics approach to enhance SC operations using real operational datasets from The Company A and best practices recommendations for its continuous improvement. The dataset referred to five years of operations of the purchases of the mechanical department and extracted from its Enterprise Asset Management (EAM) software. The company is new to BDPA applications. Thus, Advanced Analytics can prove very useful in decision-making for it. Chapter Four: Data Collection, Data Analysis, and Results.

Data Collection Process

Introduction

To understand the founded enablers, a questionnaire was developed based on the literature review. The objective of this study was to gather many answers from supply chain professionals worldwide. For these reasons, it was prepared an online questionnaire and then, the invitations were sent online through different channels such as emails, Facebook, WhatsApp, Hangouts, and LinkedIn.

Using Google Forms, the questionnaire was sent to a total of 200 enterprises; people in the companies were told to share the questionnaire internally to other professionals (in the same or related field) if possible (e.g. procurement, warehousing, transportation, etc.)

When I reached a large audience, many people did not accept the invitation to participate; some respondents answered, however, the initial contact justifying the refusal with the fact that they think they do not have the knowledge required to answer or the proficiency in the big data or analytics fields. Few answers have also been discarded because people abandoned the questionnaire before completing it; software limitations prevent the investigation from using partial answers. Thus, it got only 35 valid answers to the questionnaire.

Questionnaire on enablers for sustainable supply chain analytics (SSCA) implementation

The questionnaire was made of 29 questions, grouped in 3 main parts. The first part is the demographic part, asking for the age, the gender, the experience in the field, and more details regarding the working position. The second part is the core of the study. It contains the questions that are aimed to investigate the external and internal enablers of SSCA and big data. The third part focuses on the use of data analytics within the company.

At the end of the questionnaire, I left some blank fields for the users to give me suggestions and comments in order to receive feedback about more enablers that I did not take into account for future studies and at the same time, receive feedback regarding how I can improve the questionnaire.

As I mentioned before, this dataset contains 35 valid responses for 50 different variables that logistics and supply chain professionals consider while using or not analytics tools such as BDPA. The survey questionnaire was framed using the 5-point Likert (Abdul 2010; Leung 2011) scale.

Insights of the questionnaire on enablers for sustainable supply chain analytics (SSCA) implementation.

The survey has been running for 4 months (March 2018-July 2018) which I underlined the following insights from data. Within the large group targeted at the beginning, only 104 people viewed the questionnaire (measured through link clicks). Interestingly, while the social network audience was far bigger, it accounted for only 42% (almost half of which from the sponsored post) while direct contact brought the remaining 58%. Regarding the demographics, 23.5% of participants came from Europe, 73.5% from Latin America, around 3% from the US and the Caribbean. While these numbers are encouraging, unfortunately only 35 people completed the questionnaire. This finding is a possible indication that either the people clicked only to understand more about the questionnaire and left because they were not interested in participating or they did not complete the questionnaire because it was too long or complex for them. This last hypothesis comes from some direct feedback from known participants. I cannot confirm this on a large scale because incomplete questionnaires are not recorded by the system; this limitation will be considered in the following works. Interestingly, while participants from LATAM and Europe represented the same percentages, people from LATAM completed the questionnaire twice as much as European participants did. In other countries, both were from the Caribbean and Europe. The elements that were highlighted by participants in the free text were especially the legal framework (e.g. speed in applied regulations), lack of training skills and labor cost as enablers for sustainable supply chain analytics. They also indicated that grow scalability and compromise/integration with all management levels are important intangible assets to consider in the equation.

Data Analysis Process

The objective of this study is to understand the hidden latent factors driving the adoption of big data analytics in the supply chain. This study is unable to measure these factors directly because it is exploring what they are. For this reason, it had been used statistical techniques that can help to understand the broad concepts that define the dimensions. These hidden factors are expressed through the questionnaire answers, and the questions are the independent variables to measure.

Considering the possible statistical analysis available such as simpler statistics or machine learning, I decided to use a powerful and commonly one like it is the Exploratory Factor Analysis (EFA).

Procedures of EFA

This thesis followed the process of (Brown 2015), after determining that EFA is the most appropriate analytic technique for empirical question at hand; the researcher must decide which indicators to include in the analysis and determine if the size and the nature of the sample are suitable for the analysis. Typically, the process steps to follow on EFA include:

1. Selection of a specific method to estimate the factor model;

2. Selection of the appropriate number of factors;

3. In the case of models that have more than one factor, selection of a technique to rotate the initial factor matrix to foster the interpretability of the solution; and

4. If desired, the selection of a method to compute factor scores.

Details

To carry out the Exploratory Factor Analysis, it was used the statistical software R which is already popular in research and providing this statistical analysis. The questionnaire answers collected from "Google Forms" were downloaded in CSV format into Excel and manually checked for errors. Then, the answers of the data were reshaped in a common format used by R. After, the data was uploaded into "R" and stored for analysis. This study used "Psych" package's "fa.parallel" function on "R" to execute a parallel analysis.

Naming the Factors

After establishing the adequacy of the factors, it is time to name the factors found in the questionnaire. This is the theoretical side of the analysis where it forms the factors depending on the variable loadings got on the previous sections. The factors found were top management, data quality, technology, business size, customer engagement, etc.

Conclusions

This chapter wanted to explore the factors that affect the transformation of SSCA data in value. Thus, it had been discussed about the results that were gotten in this study from the questionnaire developed using the basic idea of EFA, covered parallel analysis and screen plot interpretation. Then, the research moved to factor analysis to achieve simple structure analysis and validate the same to ensure the model's adequacy. Later, the research arrived at the names of the factors from the variables. This research allows you to understand a better insight into the factors that can affect the adoption of big data on sustainable supply chain analytics. Distill the results that were run multiple times in EFA. This research did not find clear factors due to the few quantities of respondents. However, this research was capable to find the factors depending on the variable loadings that impact in the adoption of BDPA for SSCA, tools and techniques that enable decision making through SSCA, and the influence degree (coefficient 0.4 that was the relation between the question and the factor) of each factor for facilitating or delaying sustainability adoption that was not investigated before. The future research may focus on obtaining more inquests with more participants to be able to get a significant number of samples for a better statistical analysis.

Chapter Five: Case Study

Objectives

This research project attempts to explore the gap: “the enablers of big data that impact sustainable supply chain analytics.” Therefore, this project sets out the following objectives - specifically in the supply and purchasing department:

To investigate the role of predictive analytics in a real case scenario and at the same time to analyze whether with the use of a predictive model in a simulated environment it is also going to have a reduction in sustainable supply chain performances.

Processes in Place and Datasets

Processes

Even though a lot of information was asked to “THE COMPANY A” related to the purchasing processes under investigation, this is a mandatory preliminary step for the data analysis.

Datasets

The data file that “THE COMPANY A” provided it will constitute the structured dataset for the analysis. Currently, “THE COMPANY A” uses an Enterprise Asset Management (EAM). Based on the exchanges between the authors, “THE COMPANY A” and the online documentation, the view, and understanding of the data can be summarized as the following points:

Data were organized into two main parts: received items - related to the items arriving at the warehouse - and material issues – items removed from the inventory. In this last group, it can be distinguished the items removed for internal consumption, or items transferred to other locations. On this project, the focus is only on consumption and reception. Data were organized into commodity groups, e.g., Maintenance, Reparation; and each item – referenced with an item number and a description – is associated with one of them. Moreover, each item inbound (shipped to the warehouse) was associated with an order number, a date for the order, a responsible, a quantity and a price. Similarly, for each outbound item (taken from the inventory) it can be found a quantity and a date. Each inventory movement was also associated with a person responsible for the operation and an order number, plus some more information to relate the movement with other Maximo’s operations; however, these details are not useful for the analysis now and will not be mentioned further.

Three main batches of their system export have been received. These data are related to the orders and internal demand for different products. Extracted datasets are in the form of structured data in the common CSV file format; these files have been transferred between the parties through a well-known enterprise secure cloud to ensure confidentiality. The first one was an initial export to validate the methodology and to understand the data structure. However, the quantity and the type of data were not satisfied with any useful statistical

analysis (a few months of data related to the cafeteria commodity group). The second batch was a broader export with a longer period; this batch was used to start a data visualization approach to check the quantity in a long period of time for each item in the inventory. The last batch was a much more complete export related to the last five years of operations and was considering all the important commodity groups, specifically related to the mechanical department. While this step by step approach took a little more time compared to a single batch exchange, it was very useful to validate the methodology focused on the current operation processes – less data, less cleaning, only a few processes at a time - and choose the right tools. In the following case, carried analysis refers to this complete last batch only.

Methodology and Findings

Data analysis was conducted in two steps: a qualitative approach aimed at understanding the non-measurable big picture of the situation and a quantitative approach for measuring the metrics of interest. For both, the data have been analyzed manually through dedicated software in Python - that was developed for this task – and the well-known Elastic Search software for a standard big data approach, free on the internet.

Qualitative Approach

The qualitative approach is straightforward. As I said, I have been able to reconstruct the evolution of the quantity of each item along the five years of the dataset. The evolution was then plotted and checked visually. A similar approach has been used for checking the quantity of material ordered per single order. This last operation was done only for a random subsample of the dataset, to test the methodology on a smaller subset. So, there is no need to plot the entire dataset to validate the method.

Quantitative Approach

Quantitative analysis using big data analysis approach was used in this case study to tackle down the following points:

- To remove the visible errors
- To plan an error recovery strategy for the quantitative analysis (where possible)

The quantitative analysis processes used the following steps:

ABC Analysis

Inventory Turnover Ratio Analysis (ITR)

Interpretation of the Inventory Turnover Ratio Analysis (ITR)

Days of Inventory on Hand Ratio (DOH)

Interpretation of the DOH Analysis

Correlation Analysis or co-occurrence of orders:

Obsolescence Analysis

Case Study Conclusions

The findings from the case study enabled to identify the factors that affect the use of Big Data across their sustainable supply chain analytics and the impact of their implementation within a company. Based on the findings and analysis, a brief conclusion can be made to this case study in relation to the research questions.

What are the influence degrees of certain enablers that impact the effective implementation of BDPA on SSCA practices within companies?

- This case study allows you to understand a better insight into the factors that can affect the adoption of big data on sustainable supply chain analytics such as lack of proper training skills, lack of strong policies of use, etc. Even though, the case study by itself was not capable to get the influence degrees of certain enablers. On the other hand, the previous questionnaire in chapter 4 was capable to find the coefficient 0.4 that was the relationship between the questions and the factors obtained from the respondents' answers in compliance with the variables that impact the adoption of BDPA for SSCA.

How the use of certain tools and techniques of BDPA impacts the effectiveness of decision-making on sustainable supply chain analytics performances?

- Based on the discussions with the interviewees, the current tool that they are using by themselves cannot analyze data. The company needs more appropriate tools for the data analysis that should be compatible with their current software. MS Excel is a much-loved application, but it does not seem to be the appropriate application for the analysis of large datasets. At this point, Excel would appear to be of little help with big data analysis, and the process time of analysis will be longer, tedious, complicated, time-consuming, unstable, error-prone that will increase the workload of the employees.

How do internal practices compete with external pressure in the adoption of BDPA for SSCA policies and practices?

- Even though they are using powerful Enterprise Asset Management (EAM), it seems that they still struggle to gain value. It may be due to the contentment with the current version of the system, lack of proper training skills, or worries over cost, and selecting features of the current software. According to the research that has been done on the software, it can be affirmed that the software can make some of the tasks of an advanced analytic tool and data visualizations. But these can be costly and may not allow flexibility. Moreover, this preliminary analysis aims at understanding what the top management can do with the data before a big data approach.

- Data errors prevent an accurate analysis and measure of KPIs. Before any big data approach, the company should work in putting in place strong policies to prevent errors. If

there is some interest in exploiting current data, different approaches can be considered: first, empty item numbers should be addressed. A part of them can be recovered manually (operators can know the references) or by associating the item number with recurrent descriptions in the data (e.g., the same items could share the same description.) Secondly, data errors due to human mistake (e.g., the item number in the item quantity) are hard to recover but less hard to prevent; control tools and methods can be implemented to prevent an insertion in the database (e.g., display an error message when an operator inserts an outlier value in a field, asking to confirm this abnormal number.) However, software compatibility can be an issue for this task.

Chapter Six: General Conclusions

Introduction

This chapter provides a summary of the main findings of the thesis, its contributions, and limitations. The overall aim of the thesis identified research gaps and research questions that are revisited.

Main Contributions of the Thesis

- To propose a methodology to identify the enablers of SSCA, the necessary tools, and techniques of BDPA.
- A questionnaire was written and sent to professionals in the supply chain.
- To understand a better insight into the adoption of big data and predictive analytics.
- To identify the factors that affect the proper implementation of big data.
- To identify the coefficient relation between the questions and the factor.
- First analysis of the answer enablers to identify interest in the concepts from the respondents, but also a lack of education and training was found in these domains.

Thesis Limitation

The thesis focused on investigating how the enablers of big data and predictive analytics impact sustainable supply chain implementation and practices where this overall aim was cascaded down into three research questions. The findings of the thesis contributed to a better understanding of how big data impact the sustainable supply chain. However, the thesis has several limitations. First, the thesis selected a company that is an example in sustainable supply chain operations and a leader in the region. Although the company represented one industry, other contexts and industries may reveal different sustainable supply chain strategies and practices.

Second, the thesis relied on conducting a single case study to reveal the sustainable supply chain strategies using disruptive technologies such as Big Data and Predictive Analytics. Increasing the number of case studies may restrict to probe deeply into how the enabler of Big

Data Analytics impacts sustainable supply chain analytics practices. Although the primary and secondary sources of information in the case study provided rich information to answer the research questions, increasing the number of case studies could be useful to gain a better understanding of how big data affect various SSCA performances of the company. It may also assist in detecting more SSCA strategies and practices and providing a better understanding of how BDPA impacts SSCA. Third, the questionnaire in the thesis was confined to the company employees and external SC professionals from other areas and companies. Questioning suppliers and clients beyond the dyadic focus may reveal more insights on how BDPA impacts on SSCA.

Future Research

The thesis findings highlight some avenues for future research. The thesis focused on investigating the enablers of big data that impact sustainable supply chain analytics. Extended research may look at how big data and predictive analytics are implemented within the supply chain and spread at companies belonging to the service or public sectors. The future research may focus on revealing the applicability and limitations of the identified sustainable supply chain analytics (SSC+BDPA) strategies implementations and spread at the companies and suppliers in private and public sectors.

Another future research may be considered in the questionnaires along with the use of a broad quantity of respondents.

Résumé de Thèse

Chapitre : Introduction

Introduction

Le Big Data et l'analyse prédictive (BDPA) sont devenues cruciales pour la gestion des fonctions de la chaîne d'approvisionnement, où les processus intensifs de données peuvent être largement améliorés grâce à leur utilisation efficace. Le BDPA a émergé comme outil à la fois stratégique et opérationnel qui peut apporter des changements fondamentaux à la chaîne d'approvisionnement (SC)(Wu et al 2015;. Waller et Fawcett 2013;. Song et al 2017;. Zhao et al 2017).

Comme un atout pour la prise de décision, le BDPA peut jouer un rôle central dans la transformation et l'amélioration des fonctions de la Supply Chain. En outre, le praticien et les chercheurs se demandent comment le BDPA impacte les trois aspects de durabilité (environnementaux, économiques et sociaux) dans la chaîne d'approvisionnement.

Chapitre deux: Analyse documentaire

Les piliers de la chaîne d'approvisionnement durable : 3BL

Économique

L'objectif principal des entreprises est générer des profits. Même pour les organismes sans but lucratif, générer de l'argent est essentiel pour continuer à fonctionner. La performance économique représente la capacité de l'entreprise à offrir un rendement à ses actionnaires. Dans la littérature existante, le pilier économique dans le développement durable est généralement le mieux documenté.

Social

Même si l'accent dans les études sur le développement durable dans le SCM a été mis sur l'environnement (Ashby et al 2012;. Lee et al 2014;. Vachon et Klassen 2006a), on observe une tendance croissante à considérer la dimension sociale du développement durable. (Awaysheh & Klassen 2010) identifient les pratiques sociales et les pratiques de gestion qui affectent le développement des hommes. L'amélioration du pilier social représente une opportunité pour les entreprises d'améliorer leurs relations avec la communauté, les actionnaires, les employés et les clients (Carter & Easton 2011a, Carter & Jennings 2002).

Ecologique

Le pilier environnemental dans le développement durable a reçu beaucoup d'attention dans la littérature (Klassen & Vereecke 2012) l'objectif général de ce pilier est d'identifier l'interaction des entreprises avec l'environnement naturel. Le pilier environnemental dans le

développement durable fait référence au fait que les entreprises doivent tenir compte de leurs activités l'impact sur l'environnement et inclure ces considérations dans leurs activités et opérations quotidiennes. Les inquiétudes concernant les questions environnementales - telles que l'épuisement des ressources, la pollution, les changements climatiques, l'appauvrissement de la couche d'ozone et la gestion des déchets - ont attiré l'attention des gouvernements et des entreprises en vue de protéger l'environnement (GÖNCZ et al., 2007).

Big Data et l'Analyse Prédictive

Dans le cadre de cette analyse, ma recherche explore les technologies émergentes qui conduisent une innovation majeure et pourrait représenter des changements dans la conception d'analyse de la chaîne d'approvisionnement durable. Cette technologie c'est le BDPA. Il n'y a pas de consensus clair sur les différentes terminologies liées aux Big Data (BD) dans la littérature.

Sur la base de la nature des données, le BD a été principalement caractérisée par trois dimensions (les 3V) : 'Volume' 'Velocity' et 'Variety' (IBM 2015, Brown et al 2011; Sonka 2014 ; Gunasekaran et al 2016). Mais les 3V peuvent également être étendues à deux autres dimensions : 'Véracité' et « Value ».

La valeur de l'utilisation de la BDPA

Selon McKinsey and Company (société de conseil), le BDPA serait l'occasion pour aborder certains défis auxquels l'industrie est confrontée. Par exemple, améliorer l'expérience client, donner du sens aux grandes quantités de données non utilisées dans le commerce, améliorer les modèles et les prévisions de revenus inexactes ou trompeuses, se concentrer sur les décisions micro, etc. (Cour 2015). La collecte, le stockage et l'extraction du BDPA peut créer une valeur significative pour l'économie mondiale, l'amélioration de la productivité et de la compétitivité des entreprises et le secteur public et la création d'un surplus économique important pour les consommateurs (Manyika et al 2013; Brown et al 2011). En raison des avantages perçus du BDPA, les organisations sont très motivées pour développer leurs capacités techniques et organisationnelles pour extraire la valeur des données. Les aspects fondamentaux de génération de valeur dépendent de la capacité de l'organisme à saisir, stocker et analyser un grand volume de données complexes, générées en temps réel ou presque réel avec l'appui de l'analyse avancée (Yesudas et al. 2014). De plus, des études récentes montrent que les chaînes d'approvisionnement recueillent d'énormes quantités de données, mais que les entreprises et les praticiens sont confrontés à des difficultés extrêmes pour transformer les données en valeur (Lisa & Toby 2017; Rogers Dale 2017; Richey et al 2016b).

Supply Chain Management durable (SSCM)

Les entreprises dans les secteurs manufacturiers et de services ont connu des changements spectaculaires en termes d'activités et opérations. L'internationalisation des entreprises et de l'approvisionnement, le développement technologique rapide et le cycle de vie plus court du produit (Hutchins & Sutherland 2008, Vermeulen et Seuring 2009) sont quelques-unes des

raisons pour restructurer leurs organisations et les chaînes d'approvisionnement. Bien que les chaînes d'approvisionnement sont structurées pour obtenir des avantages économiques et concurrentiels, elles sont souvent sources de risque pour le développement durable. Par exemple, l'approvisionnement dans des pays où les coûts sont plus faibles peut permettre des avantages économiques, mais le transfert des marchandises vers l'Europe et aux Etats-Unis peut augmenter les émissions de CO2 et la consommation d'énergie (Abbasi et Nilsson 2012). En outre, les entreprises doivent éviter les problèmes sociaux et éthiques dans ces régions pour protéger l'image des marques et leurs réputations. Par conséquent, le périmètre de la mise en œuvre de la durabilité des entreprises a été étendu pour inclure les activités en amont et en aval dans leurs chaînes d'approvisionnement. Cela implique que les entreprises sont responsables de l'impact des activités de leurs fournisseurs, ainsi que du produit à travers son cycle de vie jusqu'à son élimination finale (Ashby et al 2012 ; Awaysheh & Klassen 2010, Rao & Holt 2005, Seuring & Müller 2008).

Analyse de la chaîne d'approvisionnement durable (SSCA)

La chaîne d'approvisionnement durable (SSCA) est décrite comme l'utilisation de l'analyse d'affaires dans la collecte, l'analyse et la diffusion des données relatives à la durabilité. L'objectif est la prise de décision efficace et efficiente sur les questions de développement durable (Deloitte 2013). La littérature a souligné une nécessité élevée par les organisations de gérer et de collaborer étroitement avec les fournisseurs et les clients sur les questions de développement durable (Leppelt et al. 2013) pour accomplir un meilleur contrôle des risques et une viabilité organisationnelle (Foerstl et al 2010; Paulraj 2011). A cet effet, l'analyse de la chaîne d'approvisionnement (SC) peut recueillir et analyser les données liées à la durabilité efficace et efficiente, favorisant ainsi une variété de besoins d'information qui incluent la prévision, l'analyse et l'évaluation des enjeux économiques, environnementaux et sociaux. Les organisations doivent développer et acquérir des capacités pour permettre une SC durable. Par conséquent, nous reconnaissons qu'une SCA durable exige une réflexion plus large et l'alignement entre les objectifs stratégiques et les grandes analyses de données, ainsi qu'une culture organisationnelle favorable (Richardson 2011, Ransbotham 2017. Wang et al 2016). Les chercheurs ont amélioré la relation entre les objectifs stratégiques, la culture, la transparence et la gestion des risques qui sont éléments constitutifs de la SCA durable (Ageron et al. 2013, Mello et Stank 2005 ; Gunasekaran et Spalanzani 2012). Pour activer cette relation, le BDPA pour les SSCA vient au premier plan pour assurer la collecte, le nettoyage, l'analyse et la diffusion d'informations en toute transparence entre les fonctions et les processus (IBM 2018). Cela permettra aux dirigeants d'acquérir des capacités analytiques appropriées, ainsi que les ressources appropriées nécessaires à l'adoption de SSCA pour créer de la valeur organisationnelle grâce à la réalisation des objectifs de l'organisation (Bertels 2010, Deloitte 2012). L'engagement de la direction et des cadres supérieurs est une priorité pour les organisations et les chaînes d'approvisionnement qui adoptent des pratiques durables (Foerstl et al 2015 ; Gattiker & Carter 2010).

Facteurs qui permettent la mise en œuvre le SSCA

Introduction

L’analyse de la chaîne d'approvisionnement durable (SSCA) est devenue un enjeu saillant. SSCA combine les concepts de gestion de la chaîne d'approvisionnement et la durabilité (Turker & Altuntas 2014) et implique toutes les activités des entreprises pour accroître la durabilité de leurs chaînes d'approvisionnement (Pagell et Wu 2009) avec les caractéristiques de Big Data Analytics. Comme mentionné précédemment dans la section « SCA durable »., les chercheurs ont déjà identifié plusieurs facteurs et les obstacles à la mise en œuvre réussie de SSCA (Diabat et al 2014 ; Oelze 2017). Cependant, il n'y a pas de recherche achevée qui identifie le degré d'influence de chaque facteur pour faciliter / retarder l'adoption de la durabilité (Wang et al 2016; Firouzeh et al 2017). Cette recherche vise à suivre les conseils d'autres chercheurs pour estimer les facteurs d'impact qui facilitent l’utilisation du BDPA pour le SSCA.

Facteurs du SSCA

Les Facteurs de SSCA (Walker et al 2008 ; Lin et al 2010) sont les facteurs qui motivent l'adoption de l'analyse de la chaîne d'approvisionnement durable. Ces catalyseurs sont décrits de manière générique pour toute innovation et pour cette raison ils ont été inclus dans le cadre conceptuel. L'étude met l'accent sur l'analyse des facteurs spécifiques pour SSCA, soit l’adoption de perspectives environnementales, économiques et sociales. Cette recherche a demandé un ajustement pour l’adoption de la SSC traditionnelle. Les catalyseurs identifiés sont présentés dans le tableau 3 et le tableau 4, respectivement. Ces catalyseurs ont été divisés en deux groupes (externes / internes), comme indiqué ci-dessous.

Facteurs internes

Une condition pour une mise en œuvre fructueuse des normes de SSCA est le respect des employés de l'entreprise. Les chercheurs mentionnent souvent l'engagement de la direction, mais aussi leur implication et leur soutien spécifique comme étant bénéfiques (Oelze 2017). De la même manière, une culture globale de soutien pour le développement durable, l'existence d'une mission qui focalise sur l'environnement et l'histoire d'une organisation sont reconnus comme habilitants pour la SSCA. Ceux-ci comprennent la participation des employés.

De plus, l'existence d'une stratégie de développement durable pour l'analyse de la chaîne d'approvisionnement et son alignement avec la stratégie globale de l'entreprise a été identifiée comme cruciale (Dey et al 2011 ; Hervani et al 2005). La planification stratégique de base de la mise en œuvre des politiques SSC a déjà été reconnue comme favorable à une mise en œuvre réussie (Klimley 2007). En outre, la collaboration stratégique avec le fournisseur a été définie comme le « paradigme de collaboration » qui est essentiel pour obtenir un avantage concurrentiel grâce à des analyses de la SSC(Firouzeh et al 2017 ; Mani et al 2017 ; Wang et al 2016).

Par ailleurs, des recherches antérieures ont amélioré les ressources et l'expertise des entreprises dans le cadre de habilitants pour la SSC. Plus précisément, la disponibilité des

ressources et la taille globale d'une entreprise constituent des facteurs facilitant la SSC (Alvarez et al. 2010). Par ailleurs, l'existence ou le développement des capacités liées à la durabilité et de la chaîne d'approvisionnement générale sont mis en évidence dans la littérature académique (Large & Gimenez Thomsen 2011). En particulier, cela se rapporte à la formation des personnes au sein du service d'achat (Andersen & Skjoett-Larsen 2009). De plus, les études précédentes suggèrent des preuves pour le bien d'effectuer des mesures opérationnelles pour faciliter le déploiement SSC(Sikdar 2003 ; Clift 2003). Dans le tableau 9, vous verrez les habilitants internes liés à la direction et l'utilisation de la méthodologie par chaque auteur pour atteindre leurs études.

Facteurs externes

Les facteurs externes sont fermement liés au contexte mondial dans lequel travaille l'entreprise. Sur ce point, la culture nationale d'un fournisseur peut constituer un facteur favorable à la SSCA (Ciliberti et al. 2010a). De plus, une intégration technologique et logistique des membres de la chaîne d'approvisionnement et le partage de l'information sont propices (Vachon & Klassen 2006a; Zsidisin & Hendrick 1998b). Selon cette étude, cela peut également réduire la nécessité d'audits grâce à une meilleure compréhension des processus des fournisseurs (Barratt 2004). Cependant, la SSCA est uniquement pris en charge lorsque la relation entre l'entreprise et les membres clé de la chaîne d'approvisionnement se caractérise par la confiance et la transparence (Oelze et al 2016 ; Ciliberti et al 2010b). Cela vaut notamment pour la collaboration au sein d'un secteur avec des ONG ou avec ses concurrents (Pagell et Wu 2009 ; Oelze et al 2016, Vachon et Klassen 2006b).

Conclusions

Ce chapitre a discuté de l'examen de la documentation, les lacunes de recherche identifiées, l'approche de l'interaction et les principaux concepts qui sont adoptés pour étudier comment les catalyseurs de grands impacts de données sur l'analyse de la chaîne d'approvisionnement durable. Le chapitre suivant présente et discute la méthodologie de la recherche, les questions de recherche et d'un cadre conceptuel qui est appliqué dans cette thèse.

Chapitre trois : Méthodologie de recherche

Approche de recherche

Le sujet de recherche est complexe et dynamique car il concerne l'interaction et le changement des processus internes et externes qui se déroulent dans un contexte inter-organisationnel. Dans cette thèse, une approche quantitative et qualitative basée sur des questionnaires et des études de cas est plus appropriée en raison de la nature des lacunes et des questions de recherche. L'approche avec une étude de cas a permis la collecte des données des employés de la « Société A » sur la mise en œuvre de SSC en utilisant des grandes quantités de données. D'autre part, les questionnaires ciblent des professionnels de la chaîne d'approvisionnement, en mesure d'identifier les problèmes courants dans le domaine du SC dans leurs entreprises.

La recherche présentée dans ce manuscrit a été réalisé en deux phases. La première phase a été la compréhension des facteurs.

Un questionnaire basé sur la revue de la littérature et inspiré de (Creswell 2003, Fallis 2005, Watson et al. 2004 ; Wacker 1998) a été développée. Le but de cette étude est d'obtenir au moins 35 réponses valides pour effectuer l'analyse statistique. Les participants ciblés sont des cadres supérieurs de différents pays, capables d'identifier les problèmes de la chaîne d'approvisionnement dans leurs entreprises, et qui sont responsables de SCM et étaient donc qualifiés pour fournir des réponses valables à cette recherche. Ils ont tous été invités à remplir et retourner le formulaire en utilisant les échelles de mesure de la mise en œuvre de catalyseurs de l'analyse de la SSC. Le questionnaire a été envoyé directement par courrier électronique ou par le biais des réseaux sociaux tels que Facebook et LinkedIn. Le questionnaire a ainsi touché environ 10k personnes ; cependant, la quantité de participants n'a pas été élevée, et la mesure de variables externes dans le questionnaire n'a pas été suffisamment précise (valeurs hors contrôle). Ensuite, les réponses de ce questionnaire ont été analysées avec une analyse factorielle exploratoire (EFA).

La deuxième phase consistait à réaliser une étude de cas avec une grande entreprise logistique du Panama – qu'on appellera « la société A » en raison d'un accord de non-divulgation entre l'auteur et la société - et de leurs employés. La recherche a été basée sur l'analyse d'une grande quantité de données que la société nous a fourni ; le chapitre 4 se concentrera sur l'utilité de l'analyse des données avec le BDPA pour améliorer les opérations de SC en utilisant des jeux de données réelles de la Société A et en réalisant de recommandations sur les meilleures pratiques pour leur amélioration continue. L'ensemble de données fait référence à cinq ans des opérations du service d'achat et extrait de leur logiciel Enterprise Asset Management (EAM) Maximo.

Chapitre quatre :

Processus de collecte de données

Introduction

Pour comprendre les catalyseurs, un questionnaire a été réalisé. Alors qu'un large public a été atteint, peu de personnes a participé. Certaines personnes contactées ont refusé de répondre en soulignant qu'ils pensent ne pas avoir les connaissances requises pour répondre ou les compétences nécessaires dans le domaine du BDPA. Une quantité importante des réponses ont également été mis à coté car les gens ont abandonné le questionnaire avant de le terminer ; malheureusement, certaines limitations du logiciel empêchent d'utiliser les réponses partielles. Ainsi, seulement 35 réponses valides ont été retenues pour le questionnaire.

Questionnaire sur les facteurs permettant de mise en œuvre le SSCA

Le questionnaire est composé de 29 questions, regroupées en 3 grandes parties. La première partie est la partie démographique demandant l'âge, le sexe, l'expérience dans le domaine et plus de détails sur la position de travail. La deuxième partie est la base de l'étude. Elle

contient des questions visant à enquêter sur les Facteurs externes et internes de SSCA et de grandes données. La troisième partie porte sur l'utilisation de l'analyse de données au sein de l'entreprise.

A la fin du questionnaire, un champ de libre texte a été mis à disposition des répondants afin de donner des suggestions et des commentaires, surtout en vue des études futures, et en même temps recevoir des commentaires sur la façon dont Je peux améliorer le questionnaire.

Comme mentionné précédemment, cet ensemble de données contient 35 réponses valides pour 50 variables différentes. Le questionnaire d'enquête a utilisé un échelle Likert à 5 points (Abdul 2010, Leung 2011).

Aperçus du « Questionnaire sur habilitants pour la mise en œuvre de la SSCA ».

La réalisation et l'analyse du questionnaire a pris 4 mois (juillet-2018 Mach 2018) ; les données ont souligné les résultats suivants. Du grand groupe ciblé au début, seulement 104 personnes ont visionné le questionnaire (mesuré par clics sur les liens envoyés). C'est un résultat marquant, alors que le public du réseau social était beaucoup plus important, elle ne représentait que 42% (près de la moitié du poste parrainé) tout contact direct à 58% restants. En ce qui concerne la démographie, 23,5% des participants vient d'Europe, 73,5% de l'Amérique latine, environ 3% des aux États-Unis et dans les Caraïbes. Bien que ces chiffres soient encourageants, malheureusement seulement 35 personnes ont rempli complétement le questionnaire. Ce résultat pourrait souligner que les personnes ont cliqué seulement pour comprendre mieux le questionnaire et qu'ils n'ont enfin pas participé parce pas intéressés à participer, ou qu'ils n'ont pas rempli le questionnaire car il était trop long ou complexe pour eux. Cette dernière hypothèse vient des commentaires de quelques participants connus personnellement. Je ne peux pas confirmer cela sur une grande échelle, car les questionnaires incomplets ne sont pas enregistrés par le système ; cette limitation devrait être considérée dans les recherches suivants. Fait intéressant, alors que les participants de LATAM et l'Europe représentent les mêmes pourcentages, les gens de LATAM ont rempli le questionnaire deux fois plus. Les éléments qui ont été mis en évidence par les participants dans les champs de texte libre pour les commentaires, ont été surtout le cadre juridique (la vitesse par exemple dans la réglementation appliquée), le manque de compétences de formation, et le coût du travail en tant pour l'analyse de la chaîne d'approvisionnement durable.

Processus d'analyse des données

L'objectif de cette étude est de comprendre les facteurs latents cachés qui conduisent à l'adoption du BDPA dans la chaîne d'approvisionnement. Pour cette raison, il a été utilisé des techniques statistiques qui peuvent aider à comprendre les grands concepts qui définissent les dimensions. Ces facteurs cachés sont exprimés par les réponses au questionnaire ; et les questions sont les variables indépendantes pour les mesurer.

Compte tenu de l'analyse statistique possible disponibles telles que les statistiques plus simples ou le Machine Learning, j'ai décidé d'utiliser l'analyse exploratoire (EPT), outil puissant et souvent utilisé en recherche.

Procédures de l'EPT

Cette thèse a suivi le processus de (Brown 2015), après avoir déterminé que l'EPT est la technique analytique la plus appropriée pour la question empirique à portée de main, le chercheur doit décider quels indicateurs inclure dans l'analyse et déterminer si la taille et la nature de l'échantillon sont adaptées à l'analyse. En règle générale, les étapes du processus à suivre pour l'EPT comprennent :

1. Choix d'une méthode spécifique pour estimer le modèle de facteur ;

2. Choix du nombre approprié de facteurs ;

3. Dans le cas des modèles qui ont plus d'un facteur, la sélection d'une technique permettant de faire tourner la matrice de facteur initial de favoriser l'intelligibilité de la solution ; et

4. Si on le souhaite, la sélection d'une méthode pour calculer les scores des facteurs.

Détails

Pour l'EPT a été utilisé le logiciel statistique R. Les réponses aux questionnaires recueillis de « Google Forms » ont été téléchargés au format CSV dans Excel et vérifiés manuellement contre les erreurs. Ensuite, les réponses des données ont été remodelés dans un format commun utilisé par R. Après, les données ont été téléchargées dans « R » et stocké pour l'analyse. Cette étude a utilisé « Psych » paquets « Fa.parallel » fonctionner sur « R » pour une analyse parallèle.

Nommer les facteurs

Après avoir établi le caractère adéquat des facteurs, il est temps de nommer les facteurs qu'on trouve exprimés dans les réponses au questionnaire. Ceci est la partie théorique de l'analyse où elle forme les facteurs en fonction des valeurs des variables. Les facteurs ont été trouvés la direction, la qualité des données, la technologie, la taille de l'entreprise, l'engagement des clients, etc.

Conclusions

Ce chapitre explore les facteurs qui affectent la transformation des données SSCA en valeur. Ainsi, il a été discuté des résultats obtenus dans cette étude du questionnaire mis au point en utilisant l'idée de base de l'EPT, couverte analyse parallèle et l'interprétation de l'intrigue pierrier. Ensuite, une analyse factorielle a été menée pour réaliser une analyse de structure simple et valider la même pour assurer la pertinence du modèle. Cette recherche permet d'avoir une meilleure compréhension des facteurs qui peuvent influer l'adoption du BDPA.

Distiller, les résultats qui a été exécuté plusieurs fois dans l'EPT, cette recherche n'a pas trouvé des facteurs clairs en raison des quelques quantités de répondants. Cependant, cette recherche a été en mesure de trouver les facteurs en fonction des valeurs variables qui ont une incidence sur l'adoption de BDPA pour SSCA, des outils et des techniques qui permettent la prise de décision par SSCA, et le degré d'influence (coefficient 0,4 qui était la relation entre la question et le facteur) de chaque facteur pour faciliter ou de retarder l'adoption de la durabilité qui n'a pas été étudiée auparavant. Les recherches suivantes peuvent se concentrer à obtenir plus enquête avec plus de participants pour être en mesure d'obtenir un nombre important d'échantillons pour une meilleure analyse statistique. 4 qui était la relation entre la question et le facteur) de chaque facteur pour faciliter ou de retarder l'adoption de la durabilité qui n'a pas été étudiée auparavant.

Chapitre cinq : Étude de cas

Jeux de données

Le fichier de données que « LA SOCIETE A » a fourni constituera l'ensemble de données structuré pour l'analyse. À l'heure actuelle, « LA SOCIETE A » utilise une Enterprise Asset Management (EAM).

Trois principaux lots de données ont été reçus. Ces données sont liées aux commandes et à la demande intérieure de produits différents. Ensembles de données sont extraits sous forme de données structurées dans le format de fichier CSV commun ; ces fichiers ont été transférés entre les parties par un cloud sécurisé entreprise bien connue pour assurer la confidentialité. Le premier lot était une exportation initiale des donnés de leur système pour valider la méthodologie et pour comprendre la structure des données. Cependant, la quantité et le type des données n'étaient pas satisfaisants pour toute analyse statistique utile (quelques mois de données relatives au groupe de produits de la cafétéria). Le deuxième lot était une exportation plus large avec une plus longue période ; ce lot a été utilisé pour commencer une approche de visualisation des données pour vérifier la quantité de temps pour chaque élément dans l'inventaire. Le dernier lot était une exportation beaucoup plus complète liée aux cinq dernières années d'exploitation et envisageait tous les importants groupes de produits, liés spécifiquement au service mécanique. Bien que cette approche étape par étape a pris un peu plus de temps par rapport à un seul échange de lots, il a été très utile pour valider la méthodologie, se concentrer sur les processus opérationnels actuels - moins de données, moins de nettoyage, seuls quelques processus à la fois - et a choisi les bons outils. Dans le cas suivant, l'analyse effectuée se réfère uniquement à ce dernier lot complet. Seuls quelques processus à la fois - et choisir les bons outils. Dans le cas suivant, l'analyse effectuée se réfère uniquement à ce dernier lot complet. Seuls quelques processus à la fois - et choisir les bons outils. Dans le cas suivant, l'analyse effectuée se réfère uniquement à ce dernier lot complet.

Les données ont été organisées en deux parties principales : les éléments reçus - liés aux articles qui arrivent à l'entrepôt - et les questions importantes - les éléments supprimés de l'inventaire. Ce dernier groupe peut être enlevé des éléments distinctifs pour la consommation interne, ou des articles transférés à d'autres endroits. Dans ce projet, on se concentre

uniquement sur la consommation et la réception. Les données ont été organisées en groupes de produits, par exemple, la maintenance, la réparation ; et chaque élément - référencée avec un numéro d'article et une description - est associée à l'un d'entre eux. En plus, chaque élément entrant (livré à l'entrepôt) a été associé à un numéro de commande, une date de l'ordre, un responsable, une quantité et un prix. De même, pour chaque élément sortant (retiré de l'inventaire), on peut trouver une quantité et une date. Chaque mouvement d'inventaire a également été associé à une personne responsable de l'exploitation, et un numéro de commande, ainsi que quelques informations supplémentaires pour relier le mouvement avec d'autres opérations dans Maximo ; ces détails, cependant, ne sont pas maintenant utiles pour l'analyse et ne seront pas mentionnés plus loin.

Méthodologie et résultats

L'analyse des données a été réalisée en deux étapes : une approche qualitative visant à comprendre la grande image non mesurable de la situation et une approche quantitative pour mesurer les paramètres d'intérêt. Pour les deux, les données sont analysées grâce à un algorithme qui a été développé pour cette tâche (en Python) .

Approche qualitative

L'approche qualitative est simple. Comme dit, on a été en mesure de reconstituer l'évolution de la quantité de chaque élément le long des cinq années de l'ensemble de données. L'évolution a ensuite été tracée et vérifiée visuellement. Une approche similaire a été utilisée pour vérifier la quantité de matériel commandé par commande unique. Cette dernière opération a été faite uniquement pour un sous-échantillon aléatoire de l'ensemble de données, pour tester la méthode sur un petit sous-ensemble et qu'il n'y a pas besoin de tracer l'ensemble des données pour valider la méthode.

Approche quantitative

L'analyse quantitative en utilisant grande méthode d'analyse des données ont été utilisées dans cette étude de cas pour faire face aux points suivants :

- Retirer les erreurs visibles
- Pour planifier une stratégie de récupération d'erreur pour l'analyse quantitative (si possible)

Les procédés d'analyse quantitative utilisé les étapes suivantes :

Analyse ABC

Rotation des stocks Ratio analyse (ITR)

Interprétation de l'analyse des ratios de rotation des stocks (ITR)

Jours d'inventaire sur le ratio main (DOH)

Interprétation de l'analyse DOH

Analyse de corrélation ou co-occurrence d´ordres :

Analyse des obsolescences

Conclusions de l'étude de cas

Les résultats de l'étude de cas ont permis d'identifier les facteurs catalysant l'utilisation de Big Data à travers ses analyses de la chaîne d'approvisionnement durable et l'impact de leur mise en œuvre au sein d'une entreprise. Sur la base des résultats et analyse une brève conclusion peut être faite à cette étude de cas par rapport aux questions de recherche.

Quels sont les degrés d'influence de certains outils qui ont un impact sur la mise en œuvre effective de BDPA sur les pratiques SSCA au sein des entreprises ?

- Cette étude de cas permet d'avoir une meilleure compréhension des facteurs qui peuvent influer sur l'adoption des grandes données sur l'analyse de la chaîne d'approvisionnement durable tels que le manque de compétences de formation adéquate, le manque de politiques fortes d'utilisation, etc. Bien que, l'étude de cas elle-même n'a pas été en mesure d'obtenir les degrés d'influence de certains outils. D'autre part, le questionnaire présenté au chapitre 4 avant était capable de trouver le coefficient 0,4 qui était la relation entre les questions et les facteurs se-il en fonction des charges variables qui ont une incidence sur l'adoption de BDPA pour SSCA.

Comment l'utilisation de certains outils et techniques d'impacts BDPA l'efficacité de la prise de décision sur l'analyse de la chaîne d'approvisionnement durable ?

- Sur la base des discussions avec les personnes interrogées au sein de l'entreprise A, l'outil utilisé actuellement ne peut pas analyser les données. La société a besoin d'outils plus appropriés pour l'analyse des données qui doivent être compatibles avec leur logiciel actuel.

Comment les pratiques internes influencenten concurrence avec la pression extérieure à l'adoption de BDPA des politiques et des pratiques SSCA ?

- Même si, ils utilisent un Enterprise Asset Management (EAM) puissant, il semble qu'ils ont encore du mal à gagner de la valeur. Ceci peut être dû à la satisfaction avec la version actuelle du système, le manque de compétences de formation adéquate, ou les inquiétudes sur le coût et les caractéristiques de la sélection du logiciel en cours. Selon les producteurs du logiciel, ole logiciel peut faire quelques-unes des tâches d'un outil d'analyse avancée et des visualisations de données. Mais ceux-ci peuvent être coûteuses et peuvent ne pas permettre une certaine flexibilité. De plus, cette analyse préliminaire vise à comprendre ce que la direction peut faire avec les approches Big Data.

- Les erreurs de données empêchent une analyse précise et la mesure de indicateurs de performance clés. Avant toute approche Big Data, l'entreprise doit travailler pour mettre en place des politiques fortes pour éviter les erreurs. S'il y a intérêt à exploiter les données

actuelles, différentes approches peuvent être envisagées : d'abord, la quantité de donnés manquants doit être adressée. Une partie d'entre eux peuvent être récupérés manuellement (les opérateurs peuvent connaître les références) ou en associant le numéro d'article avec des descriptions récurrentes dans les données (par exemple, les mêmes éléments pourraient partager la même description). D'autre part, les erreurs de données dus à des erreurs humaines (par exemple, le numéro d'article de la quantité de produit) sont difficiles à récupérer, mais moins difficile à éviter ; Outils de contrôle et procédés peuvent être mis en œuvre pour empêcher une insertion dans la base de données (par exemple, afficher un message d'erreur lorsqu'un opérateur d'insérer une valeur aberrante dans un champ, demandant de confirmer ce nombre anormal).

Chapitre Six : Conclusions générales

Introduction

Ce chapitre présente un résumé des principales conclusions de la thèse, ses contributions et ses limites. L'objectif général de la thèse lacunes de la recherche identifiés et les questions de recherche sont revisités. La conclusion est tirée pour enquêter sur les ***facteurs qui permettent l'analyse de Big Data et la chaîne d'approvisionnement durable***.

Principales contributions de la thèse

- Proposition d'une méthodologie pour identifier les Facteurs de SSCA, et les outils nécessaires et les techniques de BDPA.
- Proposition d'un questionnaire
- Meilleure compréhension de l'adoption des grandes données et l'analyse prédictive.
- Identification des facteurs qui affectent une bonne mise en œuvre des grandes données.
- Identification de la relation de coefficient entre les questions et le facteur.
- Première analyse des réponses des Facteurs pour identifier l'intérêt pour les concepts des répondants, mais aussi un manque d'éducation et de formation dans ces domaines a été trouvé.

Limitations de la thèse

La thèse portait sur la façon dont les enquêtes habilitantes des grandes données et les impacts d'analyse prédictive de mise en œuvre de la chaîne d'approvisionnement durable et des pratiques. Les résultats de la thèse ont contribué à une meilleure compréhension de la façon dont les grands impacts de données sur la chaîne d'approvisionnement durable. Cependant, la thèse a plusieurs limites. Tout d'abord, la thèse a choisi une entreprise qui est un exemple dans les opérations de la chaîne d'approvisionnement durable et leader dans la région. Bien que la société représentât une industrie, d'autres contextes et les industries peuvent révéler différentes stratégies de la chaîne d'approvisionnement et de pratiques durables.

En second lieu, la thèse reposait sur la réalisation d'une étude de cas unique pour révéler les stratégies de la chaîne d'approvisionnement durable en utilisant des technologies de rupture telles que Big Data et d'analyse prédictive. Bien que les sources primaires et secondaires d'information dans l'étude de cas aient fourni des informations riches pour répondre aux questions de recherche, un plus gros nombre d'études de cas pourrait être utile pour mieux comprendre la façon dont les données affectent diverses grandes performances SSCA de la société. Il peut également aider à détecter plus de stratégies SSCA et pratiques et assurer une meilleure compréhension sur la façon dont les impacts sur BDPA SSCA. Troisième, le questionnaire dans la thèse a été limitée aux employés de l'entreprise et professionnelle SC externe d'autres secteurs et entreprises. Remise en cause des fournisseurs et des clients au-delà de la mise au point dyadique peut révéler plus sur la façon des impacts BDPA sur SSCA.

La recherche future

Les résultats de la thèse mettent en évidence quelques pistes de recherche. La thèse portait sur une enquête sur les habilitants des grandes données que les impacts d'analyse de la SSC. Une recherche étendue peut regarder la taille des données et l'analyse prédictive mise en œuvre au sein de la chaîne d'approvisionnement et la propagation au sein des sociétés du service ou du secteur public. L'avenir peut se concentrer sur la recherche révélant l'applicabilité et les limites des analyses de la chaîne d'approvisionnement durable ont identifié des stratégies (SSC + BDPA) implémentations et répartis dans les entreprises et les fournisseurs dans les secteurs public et privé.

Une autre recherche future peut considérer l'utilisation d'une large quantité de répondants parce que les résultats qui ont été obtenus à partir du chapitre quatre dans cette thèse ne sont pas significatives en raison du manque de répondants et il est fortement recommandé pour les futures recherches faire plus enquête avec plus de participants.

Resumen de Tesis

Capítulo uno Introducción

Introducción

Big Data y Análisis Predictivo (BDPA por sus siglas en inglés) se han convertido en una herramienta crucial para la gestión de las funciones de la cadena de suministro, donde los procesos de manejo masivo de datos se pueden optimizar enormemente a través de su uso. (Wu et al 2015 ; Waller y Fawcett 2013 ; Song et al 2017 ; Zhao et al 2017). Además, profesiones y académicos se preguntan así mismos cómo sería el impacto de BDPA en los tres aspectos o dimensiones de la sostenibilidad (ambiental, económico y social) en la cadena de suministro.

Capítulo Dos: Revisión de la Literatura

Pilares de la sostenibilidad de la cadena de suministro: El 3BL

Económico

El principal objetivo de las empresas es ganar dinero y generar beneficios. Incluso para las organizaciones sin fines de lucro en las cuales el dinero es esencial para que continúen operando. El rendimiento económico representa la capacidad de la compañía para ofrecer una rentabilidad a sus accionistas. El pilar económico dentro de la sostenibilidad en la literatura existente es generalmente el menos entendido con respecto a los otros dos pilares. Según (Carter y Rogers 2008), el pilar económico desde la perspectiva de la sostenibilidad es difícil de obtener porque este pilar solo se enfoca por obtener ventajas competitivas y beneficios económicos.

Social

Aunque el foco sobre el medio ambiente ha dominado los estudios sobre la sostenibilidad en SCM por sus siglas en inglés (Ashby et al 2012; Lee et al 2014; Vachon y Klassen 2006a), Existe una tendencia creciente en la consideración del pilar social de la sostenibilidad. (Awaysheh y Klassen 2010), identifican las prácticas sociales como aquellas prácticas de manejo que afectan el desarrollo de las personas. La mejora en el pilar social representa una oportunidad para las empresas a mejorar sus relaciones con la comunidad, accionistas, empleados y clientes (Carter & Easton 2011a; Carter & Jennings 2002).

Ambiental

El pilar medioambiental de la sostenibilidad ha recibido mucha atención en la literatura (Klassen y Vereecke 2012) en donde el objetivo general de este pilar es identificar la interacción de las empresas con el entorno natural. La preocupación por los problemas

ambientales como el agotamiento de recursos, la contaminación, el cambio climático, la reducción de la capa de ozono, y la gestión de residuos, han logrado que se intensifique las atenciones gubernamentales y empresariales hacia la protección del medio ambiente (GÖNCZ et al. 2007). El pilar medioambiental de la sostenibilidad significa que las empresas deben considerar el impacto de sus actividades sobre el medio ambiente e incluir estas consideraciones en sus actividades y operaciones diarias.

Big Data y Predictive Analytics

Como parte de este análisis, este estudio explora la tecnología disruptiva como lo es el Big Data y Análisis Predictivo (BDPA) la cual se prevé que realice cambios potenciales en el diseño sostenible de la cadena de suministro. En la literatura actual, no hay un consenso claro sobre las diferentes terminologías y significados relacionadas con el Big Data y Análisis Predictivo, y es por esta razón que se realizó este estudio.

Big Data y Análisis Predictivo (BDPA) se caracteriza principalmente por tres dimensiones 'Volumen' (de 3 V) 'Velocidad' y 'Variedad' (IBM 2015; Brown et al 2011; Sonka 2014; Gunasekaran et al 2016). Pero aparte de las 3Vs, Big Data y Análisis Predictivo (BDPA) también se puede caracterizar por otras dos dimensiones 'Veracidad' y 'Valor'.

El valor de la utilización de Big Data y Análisis Predictivo (BDPA)

Según McKinsey and Company, Big Data y Análisis Predictivo (BDPA) sería una oportunidad para ponerse algunos retos a los que se enfrentara la industria. Por ejemplo, mejorar la experiencia del cliente, mejorar el pronóstico de la demanda etc. (Corte 2015). Esta consultora encontró que la recogida, almacenamiento y extracción de BDPA puede crear un valor significativo para la economía mundial, el aumento de la productividad y la competitividad de las empresas y el sector público (Manyika et al 2013; Brown et al 2011). Debido a los beneficios percibidos de BDPA, las organizaciones están muy motivadas para desarrollar sus capacidades técnicas y organizativas para extraer valor de los datos. Los aspectos centrales de generación de valor dependen de la capacidad de organización para capturar, almacenar y analizar grandes volúmenes de datos complejos generados en tiempo real con el apoyo de la analítica avanzada (Yesudas et al. 2014). Además, estudios recientes muestran que las cadenas de suministro ya reúnen grandes cantidades de datos, pero las empresas y los profesionales se enfrentan a dificultades extremas en la comprensión de las capacidades necesarias para transformar los datos en valor (Lisa & Toby 2017; Rogers Dale 2017; Richey et al 2016b).

La gestión de la cadena de suministro sostenible (SSCM)

Empresas en las industrias manufactureras y de servicios han sido testigos de cambios dramáticos en términos de cómo las empresas llevan a cabo sus actividades y operaciones. La internacionalización de las empresas y el abastecimiento global, el desarrollo de tecnología rápida como el 3D printing y ciclo de vida de los productos más corto (Hutchins y Sutherland 2008; Vermeulen y Seuring 2009) son algunos de los factores más influyentes que obligan a las empresas a reestructurar sus organizaciones y la cadena de suministro. Bajo estas condiciones de trabajo, las empresas cada vez alcanzan varias áreas geográficas, y esto constituye un riesgo sobre cómo cuidar de sus actividades del impacto en la sostenibilidad. A pesar de que las cadenas de suministro a veces se estructuran de manera efectiva para lograr ventajas económicas y competitivas, a menudo son fuentes de riesgo de sostenibilidad. Por ejemplo, el abastecimiento de países de bajo costo puede lograr beneficios económicos, en la transferencia de productos a Europa y los EE. UU., pero puede aumentar las emisiones de CO2 y el consumo de energía (Abbasi y Nilsson 2012). Además, las empresas deben evitar problemas sociales y éticos en esas regiones para proteger su imagen, marca y reputación. Por lo tanto, el ámbito de aplicación de sostenibilidad de las empresas se ha ampliado para incluir las actividades iniciales y finales en sus cadenas de suministro. Esto tiene implicaciones que las empresas son responsables del impacto de las actividades de sus proveedores en la sostenibilidad, así como el producto a través de su ciclo de vida hasta su disposición final (Ashby et al 2012; Awaysheh y Klassen 2010; Rao y Holt 2005; Seuring & Müller 2008). Según (Carter & Easton 2011a), "El amplio concepto de sostenibilidad, y las interfaces clave que la sostenibilidad tiene con la gestión de la cadena de suministro, sugiere fuertemente que la sostenibilidad es, en cambio licencia para hacer negocios en el siglo XXI, y la gestión de la cadena de suministro es un componente integral de esta licencia"

Sostenibilidad y la cadena de suministro analítica (SSCA)

Sostenibilidad y la cadena de suministro analítica (SSCA) se describe como el uso de análisis de negocios en la recogida, análisis, y la circulación de los datos relacionados con la sostenibilidad. El objetivo es alinear la información oportuna que puede ser utilizado para la toma de decisiones eficaz y eficiente en materia de sostenibilidad (Deloitte 2013). La literatura ha señalado la necesidad de las organizaciones para gestionar y colaborar estrechamente con los proveedores y clientes sobre los aspectos de sostenibilidad (Leppelt et al. 2013) para lograr un mejor control de los riesgos y sostenibilidad de la organización (Foerstl et al 2010; Paulraj 2011). Para este propósito, la cadena de suministro analítica puede reunir y analizar datos relacionados con la sostenibilidad con eficiencia y eficacia, lo que apoya una variedad de necesidades de información que incluyen la predicción, análisis y evaluación de los aspectos económicos, ambientales y sociales. Las organizaciones deben desarrollar y adquirir capacidades para permitir una SCA sostenible. Por lo tanto, reconocemos que SCA sostenible requiere un amplio pensamiento y la alineación entre los objetivos estratégicos y el análisis de grandes volúmenes de datos, así como la cultura organizacional (Richardson 2011; Ransbotham 2017; Wang et al 2016). Los académicos han mejorado la relación entre los objetivos estratégicos, la cultura, la transparencia y la gestión

de riesgos (Ageron, Blandine; Lavastre, Olivier; Spalanzani 2013; Mello y Apestó 2005; Gunasekaran y Spalanzani 2012). Para permitir esta relación, BDPA y SSCA se debe asegurar la recogida, limpieza, análisis, y la distribución de información sin problemas a través de funciones y procesos (IBM 2018). Es importante que los líderes entiendan el papel de SSCA para construir un formato necesario para la toma de decisiones estratégicas relacionadas con la sostenibilidad. Esto permitirá a los líderes para adquirir las capacidades analíticas apropiadas, así como los recursos correspondientes necesarios para la adopción de SSCA.

Factores y habilitadores para la aplicación de análisis de la cadena de suministro sostenible.

Introducción

SSCA se ha convertido en un tema destacado en la investigación reciente. SSCA combina los conceptos de gestión de la cadena de suministro y la sostenibilidad (Turker y Altuntas 2014) e implica todas las actividades de las empresas para aumentar la sostenibilidad de sus cadenas de suministro (Pagell y Wu 2009) junto con las características de Big Data Analytics. Como se mencionó anteriormente en la sección "SCA Sostenible". Los académicos ya han identificado varios conductores y barreras para la implementación exitosa de SSCA (Diabat et al 2014; Oelze 2017). Sin embargo, no hay ninguna investigación completa que busque identificar el grado de influencia de cada factor para facilitar o/u retrasar la adopción de BDPA en la cadena de suministro sostenible (Wang et al 2016; Firouzeh et al 2017). Esta investigación tiene como objetivo seguir el consejo de otros investigadores para estimar los factores y habilitadores para implementar Big Data y Análisis Predictivo en SSCA.

Factores de SCA Sostenible

Son los factores que motivan la adopción de la cadena de suministro analítica sostenible (Walker et al 2008; Lin et al 2010, y por esta razón, se han incluido en el marco conceptual. El presente estudio se centra en el análisis de los factores para la adopción SSCA desde perspectivas medioambientales, económicos y sociales. Este estudio busca un ajuste para la adopción sostenible de la cadena de suministro tradicional mediante el uso de los términos "gestión sostenible de la cadena de suministro; habilitadores para la cadena de suministro verde y la innovación de la cadena de suministro." Los factores identificados se muestran en la Tabla 3 y 4, del presente estudio. Tengo que señalar que en los trabajos originales eran 25 factores y se centraron en la cadena de suministro verde. Por otra parte, para este estudio, se han utilizado once (11) factores importantes que fueron divididos en dos grupos externos e internos.

Factores Internos

Un requisito para una aplicación fructífera de las normas de SSCA es el cumplimiento de las mismas por parte de los empleados de la compañía. Eruditos en la materia con frecuencia mencionan el compromiso que debe tener la alta dirección, sino también su participación y apoyo específico en estas iniciativas (Oelze 2017). De la misma manera, una cultura de apoyo global para la sostenibilidad, la existencia de una misión que se comprometa con el medio

ambiente, y la historia de una organización son reconocidos como facilitadores para la implementación de SSCA.

Además, el estado del arte nos trajo aspectos estratégicos. Por lo tanto, la existencia de una estrategia de sostenibilidad para el análisis de la cadena de suministro y su alineación con la estrategia global de la empresa han sido identificado como cruciales (Dey et al 2011; Hervani et al 2005). La planificación estratégica básica de la implementación de políticas SSC ya ha sido reconocido como propicio para una implementación exitosa (Klimley 2007). Además, la colaboración con proveedores estratégicos se ha definido como el "paradigma de colaboración" que es esencial para lograr una ventaja competitiva a través de análisis de la cadena de suministro sostenible (Firouzeh et al 2017; Mani et al 2017; Wang et al 2016).

Por otra parte, la disponibilidad de recursos y el tamaño total de una empresa constituyen también los factores para la implementación de SSCA, ya que determinan el posible esfuerzo de las iniciativas de sostenibilidad de una empresa (Álvarez et al. 2010). Además, la existencia o desarrollo de capacidades relacionadas con la sostenibilidad y la cadena de suministro en general se destacan en la literatura (Grande y Giménez Thomsen 2011). Además, los estudios anteriores sugieren evidencia para así realizar métricas operativas como un factor para SSCA (Sikdar 2003; Clift 2003).

Factores Externos

Los factores externos están firmemente relacionados con el contexto global en el que una empresa funciona. En este punto, la cultura de un proveedor puede constituir un factor facilitador de SSCA (Ciliberti et al. 2010a). Por otra parte, una integración tecnológica y logística de los miembros de la cadena de suministro y el intercambio de información pueden conducir a implementar con éxito (Vachon y Klassen 2006a; Zsidisin y Hendrick 1998b). De acuerdo con esto también puede reducir la necesidad de auditorías a través de una mejor comprensión de los procesos de los proveedores (Barratt 2004). Sin embargo, SSCA sólo se admite cuando la relación entre la empresa focal y sus miembros de la cadena de suministro se caracteriza por la confianza y la transparencia (Oelze et al 2016; Ciliberti et al 2010b).

Capacidad de Absorción

La relevancia de las capacidades dinámicas (DCs por sus siglas en Ingles), específicamente la capacidad de absorción como factor moderador y requisito previo para la implementación de la innovación. (Kabir y Carayannis 2013; Wang et al. 2015; Wamba et al. 2017; Arunachalam et al. 2017). Estudios que relacionan los DCs con las prácticas de SSCM, y las influencias de las DCs en la creación de innovación (Beske 2012; Čiutienė & Thattakath 2014) Sin embargo, muchas grandes empresas aún no implementan BDPA debido a la falta de las capacidades adecuadas (Assink 2006; Čiutienė & Thattakath 2014).

Conclusiones

En este capítulo se discute el enfoque de interacción y los principales conceptos que se adopten para el estudio de cómo los factores de Big Data y Análisis Predictivo impactan sobre

la cadena de suministro analítica sostenible (SSCA siglas en ingles). Al final de este estado del arte, las preguntas de investigación y el marco conceptual se presentan y se discuten en relación con la revisión de la literatura y las lagunas u oportunidades de investigación identificadas. El siguiente capítulo trata sobre la metodología de la investigación que se aplica en esta tesis.

Capítulo Tres: Metodología de la Investigación

Enfoque de la investigación

"La investigación de los factores de Big Data y Análisis Predictivo que impactan a la cadena de suministro sostenible." Es complejo y dinámico, ya que tiene que ver con la interacción y el cambio de los procesos internos y externos que tienen lugar dentro de un contexto interorganizacional. Un enfoque cuantitativo y cualitativo basado en cuestionarios y estudios de casos son más apropiados para esta tesis debido a la naturaleza de las lagunas u oportunidades de investigación encontradas. El caso de estudio ha permitido la recogida de datos de los empleados de "La Compañía A". Por otra parte, el cuestionario desarrollado en este estudio fue dirigido a profesionales de la cadena de suministro, capaces de identificar los problemas más comunes en su campo de trabajo cotidiano.

La investigación presentada en este manuscrito se llevó a cabo en dos fases. La primera fase fue entender los factores. Basado en la revisión de la literatura, un cuestionario fue desarrollado en Google forms (Creswell 2003; Fallis 2005; Watson et al 2004; Wacker 1998) (bit.ly/enablers_ssc_questionnaire). Como las visitas in situ no eran posibles, el cuestionario se envió directamente por correo electrónico, mensajería instantánea (por ejemplo, WhatsApp y Facebook Messenger), y a través de redes sociales como LinkedIn y Facebook. La audiencia de los grupos de redes sociales fue de alrededor de 10k personas; Sin embargo, la cantidad de personas alcanzadas realmente no se pudo medir con eficacia porque había muchas variables externas que estaban fuera del control de la investigación. El objetivo de este estudio es obtener al menos 35 respuestas válidas para llevar a cabo el análisis estadístico. Los participantes objetivo fueron altos ejecutivos de diferentes países, capaces de identificar los problemas que padecen sus cadenas de suministro a la que pertenecen sus empresas, y por lo tanto fueron calificados para proporcionar una respuesta válida a esta investigación. Todos ellos se les pidió que completaran y enviaran el formulario de preguntas con escalas de medición de los factores de la implementación de la cadena de suministro analítica sostenible. Las respuestas de este cuestionario se analizarán con análisis exploratorio factorial.

La segunda fase consistió en la realización de un caso de estudio con una compañía panameña y sus empleados en el que se denominó "La empresa A" debido a un acuerdo de confidencialidad entre el autor y la compañía. El proceso de análisis se basó en el análisis de una cantidad de datos considerable (por ejemplo, artículos masivos) que la empresa nos proporciona; el capítulo 4 se centrará en la utilidad de análisis de datos con un enfoque de big data para mejorar las operaciones de SC utilizando conjuntos de datos reales de la compañía A. El conjunto de datos utilizados fue de cinco años de operaciones del departamento de compras extraídos de su software de gestión de activos (EAM siglas en inglés) Máximo. Cabe

destacar que la compañía es nueva en el uso de las aplicaciones BDPA, y de ser exitosa su aplicación puede resultar para ellos muy útil en la toma de decisiones.

Proceso de recopilación de datos

Introducción

Para entender los factores establecidos, he preparado un cuestionario que fue desarrollado en base a la revisión de la literatura. El objetivo de este estudio fue recopilar respuestas de profesionales de la cadena de suministro en varios países. Por esta razón, se preparó un cuestionario en línea y luego se envió las invitaciones a través de diferentes canales, tales como: mensajes de correo electrónico, Facebook, WhatsApp, Hangouts y LinkedIn.

El cuestionario desarrollado en Google Forms se envió a un total de 200 empresas. También se les dijo a las personas que compartieran el cuestionario internamente a otros profesionales (en el mismo campo relacionado) si es posible (por ejemplo, adquisición, almacenamiento, transporte, etc.)

Muchas personas no aceptaron la invitación a participar. Algunos de los encuestados, sin embargo, respondieron negativamente justificando que no tienen los conocimientos necesarios para responder el cuestionario. Algunas respuestas también se han descartado porque las personas abandonaron el cuestionario antes de terminarlo; las limitaciones del Google Forms impiden el uso de las respuestas parciales. Por lo tanto, sólo 35 respuestas válidas se obtuvieron del cuestionario.

Cuestionario sobre los factores para la cadena de suministro analítica sostenibles (SSCA).

El cuestionario constaba de 29 preguntas, agrupadas en 3 partes principales. La primera parte es la parte demográfica, en donde se solicitaba la edad, el género, la experiencia en el campo, y más detalles con respecto a la posición de trabajo. La segunda parte es el núcleo del estudio. Está contiene las preguntas dirigidas a investigar los factores externos e internos de SSCA y Big Data y Análisis Predictivo. La tercera parte se centra en el uso de Big Data y Análisis Predictivo dentro de la empresa.

Al final del cuestionario se colocaron algunos campos en blanco para que los usuarios puedan dar sugerencias y comentarios, con el fin de recibir información sobre más factores que puedan ser tomados en cuenta para futuros estudios, y al mismo tiempo recibir retroalimentación con respecto a cómo se pueda mejorar el cuestionario.

Como se mencionó antes, se obtuvo 35 respuestas válidas para 50 variables diferentes que profesionales de la cadena de suministro consideran importante para el uso de herramientas de análisis tales como el BDPA. La escala utilizada en el cuestionario es la de Likert de 5 puntos (Abdul 2010; Leung 2011).

La encuesta se realizó durante 4 meses (Mach 2018-julio de 2018), y se obtuvo lo siguiente: sólo 104 personas vieron el cuestionario (medida obtenida a través de clics de enlace). Curiosamente, mientras que el público de las redes sociales era mucho más grande, representó

sólo el 42%, mientras que el de contacto directo trajo el 58% restante. En cuanto a los datos demográficos, un 23,5% de los participantes provenían de Europa, el 73,5% de América Latina, alrededor del 3% de los EE.UU. y el Caribe. Si bien estas cifras son alentadoras, por desgracia, sólo 35 personas completaron el cuestionario. Este hallazgo es una posible indicación de que las personas que han hecho clic sólo entraron para entender más sobre el cuestionario y se fueron porque no estaban interesados en participar, o que no completaron el cuestionario porque era demasiado largo o complejo para ellos. Esta última hipótesis proviene de la retroalimentación directa de los pocos participantes conocidos. No puedo confirmar esto a gran escala debido a que los cuestionarios incompletos no son registrados por el sistema; esta limitación se considerará en las obras siguientes. Curiosamente, mientras que los participantes de LATAM y Europa representaban los mismos porcentajes, la gente de LATAM completaron el cuestionario dos veces más que Europa. Los elementos que fueron destacados por los participantes en los campos de texto libre fueron especialmente el marco legal (por ejemplo, la velocidad en las regulaciones aplicadas), la falta de habilidades de entrenamiento, y los costos laborales como factores para análisis de la SSCA.

Proceso de Análisis de Datos

El objetivo de este estudio es comprender los factores latentes que impulsan la adopción de BDPA en SSCA. Este estudio es incapaz de medir estos factores directamente, ya que está explorando lo que son. Por esta razón, se ha utilizado técnicas estadísticas que pueden ayudar a entender los conceptos generales que definen las dimensiones. Estos factores ocultos se expresan a través de las respuestas del cuestionario; y las preguntas son las variables independientes.

Teniendo en cuenta los posibles análisis estadísticos disponibles, se decidió usar análisis factorial exploratorio (EPT por sus siglas en inglés).

Procedimientos de la EFA

Esta tesis se inspiró en el trabajo de (Brown 2015). Después de determinar que la EFA es la técnica analítica más apropiada, el investigador debe decidir qué indicadores debe incluir en el análisis y determinar si el tamaño y la naturaleza de la muestra son adecuados para el análisis. Típicamente, las etapas del procedimiento del EFA incluyen:

1. Selección de un método específico para estimar los factores;

2. Selección de la cantidad apropiada de factores;

3. En el caso de los modelos que tienen más de un factor, es importante seleccionar una técnica para obtener una matriz de factores para fomentar la interpretabilidad de la solución.

4. Si se desea, se puede también seleccionar un método para calcular las ponderaciones de los factores.

Detalles

Para llevar a cabo el análisis factorial exploratorio, he utilizado el software estadístico R. Las respuestas del cuestionario recogidos en “Google Forms” fueron descargados en formato CSV en Excel y se cotejo manualmente la posibilidad de existencia de errores. Una vez verificado y corregido errores, se procedió a cargar los datos en “R” y se almacena para su análisis. Este estudio utilizó "Psicoanalizar" El paquete de “Fa.parallel” que funciona en “R” para ejecutar análisis paralelo.

Nombrando a los Factores

Después de establecer la adecuación de los factores, es hora de nombrar los mismos de acuerdo con lo que fue encontrado en el cuestionario. Este es el lado teórico del análisis donde se forman los factores que dependen de las cargas variables que se obtuvieron en las secciones anteriores. Entre los factores encontrados tenemos: Tamaño del Negocio, Compromiso de parte del cliente, Alta Gerencia, Tecnología, Calidad de Datos, Experiencia entre otros.

Conclusiones

Este capítulo se exploraron los factores que afectan la transformación de los datos de SSCA en valor. Por lo tanto, se discutió sobre los resultados que se obtuvieron en este estudio a partir del cuestionario desarrollado utilizando la idea básica de la EFA, se realizó un análisis paralelo y la interpretación del diagrama. Luego, la investigación pasó al análisis factorial para lograr un análisis de estructura simple y validarlo para garantizar la adecuación del modelo. Posteriormente, la investigación llegó a los nombres de los factores de las variables. Esta investigación permitió comprender mejor los factores que pueden afectar la adopción de Big Data en el análisis de la cadena de suministro analítica y sostenible. Sin embargo, los resultados que fueron ejecutados varias veces con el EFA, no se encontraron factores claros debido a las pocas cantidades de encuestados. A pesar de esto, la investigación fue capaz de encontrar los factores según las variables que impactan la adopción de BDPA para SSCA, las herramientas y técnicas que permiten la toma de decisiones a través de SSCA y el grado de influencia (coeficiente 0.4 que fue la relación entre la pregunta y el factor) de cada factor para facilitar o retrasar la adopción de sostenibilidad que no ha sido investigado con anterioridad. Para investigaciones futuras pueden centrarse en obtener más participantes para poder obtener un número significativo de muestras para un mejor análisis estadístico.

Capítulo Cinco: Caso de Estudio

Objetivos

Este proyecto de investigación trata de explorar la brecha o la oportunidad de: “los factores de Big Data y Análisis Predictivo y el impacto de estos sobre la cadena de suministro analítica sostenible.” Este proyecto, por tanto, establece los siguientes objetivos:

investigar el papel del análisis predictivo en un escenario real, y al mismo tiempo analizar si con el uso del modelo de predicción en un entorno simulado se puede obtener reducciones en los indicadores de la cadena de suministro analítica sostenibles. Ejemplo:

Una reducción en los residuos ((ratio de reciclaje) kg / (m2 a)),

Las reducciones en los costos logísticos y de suministro.

Procedimientos Implantados y Conjuntos de datos

Procesos

"La empresa a" facilito la mayor cantidad de información posible en relación con los procesos de compra; este es un paso preliminar obligatorio para el análisis de datos.

Conjuntos de datos

Actualmente, "La empresa A" utiliza software de IBM Máximo como gestión de activos empresariales (EAM por sus siglas en ingles). Sobre la base de los intercambios que tuve con "La empresa A", la documentación en línea, y mi punto de vista; la comprensión de los datos se puede resumir como:

Los datos se organizan en dos partes principales: - artículos relacionados con los artículos que llegan al almacén - y materiales - artículos retirados del inventario. En este último grupo, puede ser artículos distintivos retirados para el consumo interno, o transferidos a a otros lugares. En este proyecto, que se centra sólo en el consumo y la recepción. Los datos se organizan en grupos de productos, por ejemplo, mantenimiento, reparación; y cada artículo - referenciados con un número de orden y una descripción - se asocia a uno de ellos. Además, cada elemento de entrada (que se envía al almacén) se asoció con un número de orden, la fecha de la orden, un responsable, una cantidad y un precio. Del mismo modo, para cada elemento saliente (tomado del inventario) se puede encontrar una cantidad y una fecha. Cada movimiento de inventario también se asoció con una persona responsable de la operación, y un número de orden.

Se han recibido tres lotes principales de Máximo. Estos datos se relacionan con los pedidos y la demanda interna de productos. El conjunto de datos extraídos es en forma de datos estructurados en el formato de archivo CSV; estos archivos se han transferido entre las partes a través de una nube segura bien conocida para asegurar la confidencialidad. La primera fue una exportación inicial para validar la metodología y de entender la estructura de datos. Sin embargo, la cantidad y el tipo de los datos no eran satisfactorios para un análisis estadístico útil (pocos meses de datos relacionados con grupo de productos básicos cafetería). El segundo lote fue una exportación más amplia con un período más largo; Este lote se utilizó para iniciar un enfoque de visualización de datos. El último lote era una exportación mucho más completa en relación con los últimos cinco años de operaciones y consideraba todos los grupos de productos básicos importantes, relacionadas específicamente con el departamento de mecánica. El análisis realizado se refiere sólo a este último lote.

Metodología y resultados

El análisis de datos se realizó en dos etapas: una aproximación cualitativa tuvo como objetivo comprender el panorama general no medible de la situación y un enfoque cuantitativo para medir las métricas de interés. Por tanto, se han analizado los datos manualmente a través de Python y Elastics.

Enfoque Cualitativo

El enfoque cualitativo es sencillo. Como se ha dicho, este estudio he sido capaz de reconstruir la evolución de la cantidad de cada elemento a lo largo de los cinco años del conjunto de datos proporcionados. Un enfoque similar se ha utilizado para el control de la cantidad de material ordenado por pedido individual. Esta última operación se realiza solamente en una submuestra aleatoria de la base de datos, para poner a prueba la metodología en un subconjunto más pequeño así que no hay necesidad de trazar todo el conjunto de datos para validar el método.

Enfoque Cuantitativo

Se utilizó el análisis cuantitativo con enfoque de Big Data y Análisis Predictivo para abordar los siguientes puntos:

Quitar los errores visibles

Planificar una estrategia de recuperación de errores para el análisis cuantitativo

Los procesos de análisis cuantitativo utilizan los siguientes pasos:

Análisis ABC

Relación de rotación de inventario Análisis (ITR)

Interpretación del análisis de relación de rotación de inventario (ITR)

Días de Inventario de Relación de mano (DOH)

Interpretación del análisis DOH

Análisis de correlación o concurrencia de órdenes:

Análisis de la obsolescencia

Conclusiones del caso de estudio

Los hallazgos del caso de estudio permitieron identificar los factores que afectan el uso de Big Data en la cadena de suministro analítica sostenible, y el impacto que conllevaría su implementación dentro de las empresas. Sobre la base de los hallazgos y el análisis, se puede hacer una breve conclusión de este caso de estudio en relación con las preguntas de la investigación.

¿Cuáles son los grados de influencia de ciertos habilitadores que afectan la implementación efectiva de BDPA en las prácticas de SSCA dentro de las empresas?

- Este caso de estudio permite comprender mejor los factores que pueden afectar la adopción de Big data en la cadena de suministro sostenible, como por ejemplo la falta de habilidades adecuadas, la falta de capacitación en nuevas tecnologías, la falta de políticas de uso sólidas, etc. Aunque el caso de estudio por sí solo no fue capaz de obtener los grados de influencia de ciertos facilitadores. Por otro lado, el cuestionario en el capítulo 4 presentado anteriormente si fue capaz de encontrar el coeficiente 0.4 que no es más que la relación entre las preguntas y los factores que se obtuvieron de las respuestas de los encuestados según las variables que impactan en la adopción de BDPA SSCA.

¿Cómo afecta el uso de ciertas herramientas y técnicas de BDPA a la eficacia de la toma de decisiones en el análisis de la cadena de suministro sostenible?

- Sobre la base de las discusiones con los encuestados, la herramienta actual que la empresa en estudio está utilizando por sí sola no puede analizar los datos. La empresa necesita herramientas más adecuadas para el análisis de datos que deben ser compatibles con su software actual. MS Excel es una aplicación muy apreciada, pero no parece ser la aplicación adecuada para el análisis de grandes conjuntos de datos. En este punto, Excel parecería ser de poca ayuda con el análisis de Big data, ya que el tiempo de proceso del análisis sería más largo, tedioso, complicado, lento, inestable, y propenso a errores lo cual traería como consecuencia un aumento en la carga de trabajo de los empleados.

¿Cómo compiten las prácticas internas con la presión externa en la adopción de BDPA para las políticas y prácticas de SSCA?

- Aun así, la empresa está utilizando una poderosa herramienta para su manejo de datos; todavía tienen dificultades para obtener valor de este, debido a la falta de habilidades adecuadas, falta de capacitación o de las preocupaciones sobre el costo y la selección de características adicionales del software actual. De acuerdo con la investigación que se ha hecho sobre el software, se puede afirmar que el software puede realizar algunas de las tareas de las herramientas avanzadas de análisis y visualizaciones de datos. Pero estos pueden ser costosos y pueden no permitir la flexibilidad. Además, este análisis preliminar apunta a comprender qué puede hacer la alta gerencia con los datos antes de que decidan un enfoque de utilización de Big Data.

- Los errores de datos impiden un análisis preciso y a la medida de los indicadores de desempeño (KPIs por su sigla en inglés). Antes de cualquier enfoque de Big Data, la empresa debe trabajar para implementar políticas sólidas para evitar errores. Si hay interés en explotar los datos actuales, se pueden considerar diferentes enfoques: primero, deben abordarse los números de elementos vacíos. Una parte de ellos se puede recuperar manualmente (los operadores pueden conocer las referencias) o asociando el número de artículo con descripciones recurrentes en los datos (por ejemplo, los mismos elementos podrían compartir

la misma descripción). En segundo lugar, los errores de datos debidos a errores humanos son difíciles de recuperar, pero menos difíciles de prevenir; se pueden implementar controles y métodos con las herramientas adecuadas para evitar una inserción en la base de datos. Sin embargo, la compatibilidad del software puede ser un problema para esta tarea.

Capítulo Seis: Conclusiones Generales

Introducción

Este capítulo proporciona un resumen de los principales hallazgos de la tesis, sus contribuciones y limitaciones. El objetivo general de la tesis identificó las lagunas de investigación y las preguntas de investigación. La conclusión se extrae de investigar los factores de Big Data y Análisis Predictivo, y que afecta a la cadena de suministro analítica sostenible. El capítulo incluye algunas implicaciones metodológicas y las limitaciones de la tesis. Se discuten las vías para futuras investigaciones y la tesis finalizan con una conclusión final.

Principales aportaciones de la tesis.

- Proponer una metodología para identificar los factores de SSCA, y las herramientas y técnicas de BDPA.
- Se realizó un cuestionario y se envió a los profesionales de la cadena de suministro.
- Comprender una mejor perspectiva de la adopción de Big Data y análisis predictivo.
- Identificar los factores que afectan una adecuada implementación de Big Data.
- Identificar la relación de coeficiente entre las preguntas y los factores encontrados.
- Un primer análisis de las respuestas del cuestionario para identificar el interés de los factores, y los conceptos de SSCA y BDPA, pero también se encontró una falta de conocimiento y formación en estos dominios.

Limitación de la tesis

En primer lugar, la tesis selecciona una empresa que es un ejemplo en operaciones de la cadena de suministro y líder en la región. Aunque la empresa representaba una sola industria, otras industrias y compañías pueden revelar diferentes estrategias y prácticas de la cadena de suministro. En segundo lugar, la tesis se basó en la realización de un caso de estudio único para revelar las estrategias de la cadena de suministro sostenible analítica utilizando BDPA, aumentando el número de casos de estudio podría ser útil para obtener una mejor comprensión de cómo BDPA afecta a diversas actuaciones de SSCA de la empresa. También puede ayudar en la detección de más estrategias y prácticas de SSCA y proporcionar un mejor entendimiento sobre cómo BDPA impacta en SSCA. En tercer lugar, el cuestionario en la tesis se limita a los empleados de la compañía y profesionales de SC externos de otras áreas y

empresas. Cuestionando proveedores y clientes más allá del enfoque diádico puede revelar más ideas sobre cómo los impactos sobre BDPA en SSCA.

Investigación Futura

Los resultados de esta tesis destacan algunas vías para futuras investigaciones. La tesis se centró en investigar los factores de BDPA y el impacto sobre SSCA. Una investigación futura podría centrarse en poner en práctica la aplicabilidad y limitaciones de los análisis identificados y difundir las estrategias en empresas y proveedores de servicio en los sectores públicos y privados.

Otra investigación futura puede tomar en cuenta una muestra mayor de los encuestados ya que los resultados que se obtuvieron no fueron significativos debido a la falta de estos, y se recomienda enérgicamente para futuras investigaciones trabajar con más participantes. Por último, también es recomendable para futuras investigaciones, tomar en cuenta la dimensión pedagógica.

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Chapter One: Introduction

1. Introduction

The main objective of this project is to explore the enablers of big data and predictive analytics that impact sustainable supply chain within a company that has not been investigated in depth.

Big Data and Predictive Analytics (BDPA) has become crucial for managing supply chain functions where intensive data processes can be vastly improved through their effective use. BDPA has emerged as both a strategic and operational tool that may bring fundamental changes to the supply chain (SC) (Wu et al. 2015; Waller and Fawcett 2013; Song et al. 2017; Zhao et al. 2017). As stated by (Fawcett et al. 2011; Assink 2006), advances in information technology enabled the supply chain revolution. Nowadays, data is so easy to collect (e.g., RFID, barcodes, loyalty cards) and a low-cost for the stores, that big data analytics is enabling a new source of customer intimacy and competitive advantage.

As an asset for decision-making, BDPA can play a pivotal role in transforming and improving the functions of Supply Chain, for example, demand planning, purchasing or forecasting (Davenport 2014; Papadopoulos et al. 2015; Arunachalam et al. 2017; Waller and Fawcett 2013). In this changing business environment, business leaders prefer to take decisions counting in mind the data-driven insights rather than relying on their institutions (Waller & Fawcett 2013; Davenport 2014). In addition, BDPA has the capability of transforming the decision-making process by allowing enhanced visibility of firms' operations and improved performance measurement mechanisms (McAfee & Brynjolfsson 2012). For example, according to (Marr 2016) Walmart, the largest retailer chain in the world and the world's largest company by revenue with over two million employees and 20,000 stores in 28 countries, is using BDPA to drive supermarket performances. In 2015, the company announced that they were in the process of creating the world's largest private data cloud to enable the processing of 2.5 petabytes of information every hour. In order to understand their customer needs and provide them with the products they wanted to buy, Walmart and their Fast-Big Data Team create Data Café. At the Café, the analytic team has been capable to monitor 200 streams of internal and external data in real-time including 40 petabytes of recent transactional data to be modeled rapidly, manipulated and visualized. In an interview, about Walmart's project using Big Data, senior statistical analyst Naveen Peddamail said, *"If you can't get insights until you've analyzed your sales for a week or a month, then you've lost sales within that time* (Marr 2018; Marr 2016)*."* Therefore, quick access to insights is vital. For example, Peddamail mentioned in this interview about the grocery team who could not understand why sales had suddenly declined in a particular product category. By drilling into the data, they were quickly able to see that pricing miscalculations had led to the products being listed at a higher price than they should have been (Marr 2018; Marr 2016). He also mentioned that the system provides automated alerts, so, when metrics fall below a set threshold in any department, the relevant team is alerted so that they can find a fast solution (Marr 2016; Marr 2018). Furthermore, as 200 billion rows of transactional data, the Café pulls in information

from 200 sources, including meteorological data, economic data, Nielsen data, telecom data, social media data, gas prices, and local events databases. Anything within these vast and varied datasets could hold the key to the solution to a specific problem and Walmart's algorithms are designed to blaze through them in microseconds to come up with real-time solutions (Marr 2017).

BDPA becomes a competitive necessity for the management of supply chains with practitioners and scholars focused almost entirely on how BDPA is used to increase just the economic aspect (Chen et al. 2012); and they are wondering how BDPA impacts the three sustainability aspects (environmental, economic, and social) in Supply Chain. (Wang et al. 2016) brought the term Sustainable Supply Chain Analytics (SSCA) to combine the techniques of BDPA applied to Sustainable Supply Chain. He defined SSCA to the use of methodologies and techniques to collect, analyze, disseminate, and use sustainability-related information for both strategy and operations. However, there is limited understanding of the role of BDPA and SSCA as the connection or the link that enables in the format needed for taking strategic decisions related to sustainability (Wang et al. 2016; Firouzeh et al. 2017). For these reasons, this issue was chosen for this study. This research addresses the gap to explore the enablers/factors of big data that impacts on sustainable supply chain analytics addressing the following research questions:

1. ***How the use of certain tools and techniques of BDPA impact the effectiveness of decision-making on sustainable supply chain analytics performances?***
2. ***What are the influence degrees of certain enablers that impact the effective implementation of BDPA on SSCA practices within companies?***
3. ***How do internal practices compete with external pressure in the adoption of BDPA for SSCA policies and practices?***

That will be explored through a structured remote questionnaire and a case study by targeting highly experienced supply chain professionals and companies in the same area of study. Later, it will proceed to analyze the data collected, for example, identification of the leading enabler using exploratory factor analysis (EFA).

1.1 The importance of Sustainability in the Society and Organizations

According to (Faber et al. 2005), sustainability holds several meanings and interpretations. The sustainability word can be understood as the capacity to maintain or to endure and adapt (Starik & Kanashiro 2013). Sustainability has gained momentum and wide consideration from the public and private sectors during the last decade (Meqdadi 2015). Currently, a new literature vein creates a link between sustainability and the recently widespread phenomena of Big Data and Supply Chain Analytics (SCA) (Brown & Wilmanns 2014; Zhu et al. 2012; Beske & Seuring 2014).

The industrial sector has received a lot of attention due to its considerable impact on sustainability throughout the years (Schaltegger & Wagner 2011a). The Industrial

Revolution marks a major turning point in history; almost every aspect of daily life was influenced in some way. The industrial development of the past 250 years has brought immeasurable wealth, comfort, material goods, and prosperity (Shrivastava 1995; Lucas 2002). Some economists say that the major impact of the Industrial Revolution was getting a standard of living (Feinstein 1998). However, it has also caused an undesirable environmental degradation (Johnson et al. 1997). As a result, the earth is facing many problems, such as global warming, ozone depletion, deforestation and desertification, declining biodiversity, acid rain, industrial accidents, water degradation, and toxic wastes (Kardol et al. 2010; MacDonald 2010; Guerrini 2009; United Nations 2005; Shrivastava 1995). These problems are expected to aggravate in the next 35 years when the world population will double to 11 billion in 2050 (Melorose et al. 2015). To provide basic amenities to this population using current technologies, world economic production will need to increase approximately five times today's level. This can only get worse in our environmental problems (Commoner 1992; Herman & Cobb 1990). Fortunately, there is some awareness of the sustainability impact of goods and services. According to the (Ethical Consumer Report 2012), 50 percent of consumers surveyed have avoided a product based on a company's responsible reputation. This is just a little proof that there are internal and external pressures that may push industries and organizations (large and small) to change and make improvements in their processes, objectives, and policies. (Hassini et al. 2012) mentioned that their nine major factors for adoption of sustainable practices are coming from:

1. Consumers, retailers, OEMs, stakeholders who may demand products considered environmentally friendly from suppliers.

2. Governments intervention by imposing regulations and laws.

3. Science and Technology that involve the use of materials and processes not toxic, use less energy without compromising use.

4. Product Development, the greening of the existing product (e.g., recycled content, biodegradable materials, design for disassembly).

5. Process Capability, the process of producing the product will have to be environmentally capable.

6. Sourcing and Operations, many companies are joining forces with their suppliers to engage in green sourcing practices. Patagonia, for example, had a long list of sustainability-related innovations from introducing recycled polyester in premium outdoor products to converting all of its cotton fabrics to certified organic fiber. To obtain this, Patagonia had to work closely with suppliers across all supply chain levels (Brown & Wilmanns 2014).

7. Transport and Logistics. Example: Reverse logistics and return management are very specific disciplines that often get lumped into the broader ecosystem of generalized supply chain activities, e.g. FedEx, UPS, DHL (Roach 2012).

8. Marketing and Public Relations, refer to the efforts of companies to start sharing their green practices in a credible way, e.g., Coca Cola and PepsiCo are using fleets of hybrid vehicles (The Coca-Cola Company 2011; Knight 2009), and Dell campaign "Plant a tree for me Today" in where they are committed to planting 1 million trees by 2020 to reduce greenhouse gas emissions (Dell 2016). All these actions are valid efforts to cut environmental impact but, while these claims may be true, companies need to be careful to avoid "greenwash". Otherwise, NGOs such as Greenpeace and Amnesty can run boycotts in order to shame the company into offering misleading advertising (Coles 2016).

9. Social Issues focus more on the existing behavior and practices of companies in relation to the social and working conditions of their employees.

Over the last decade, corporate social responsibility and sustainability have occupied a prominent place on the global corporate agenda with an ever-increasing number of corporations engaging in responsible and sustainable business practices to create social and business value (Merrill-Sands & Du 2016). Nevertheless, we saw that every few years a severe, high-profile corporate ethical scandal occurs, capturing the attention of the media and damaging the public's trust in the corporations and their social accountability. For example, Volkswagen's emissions scandal in 2015. This example represents how greenwashing and bad business practices can erode business integrity and brand reliability. On Monday, January 4th, 2016, the U.S. justice department sued Volkswagen in federal court, questioning Volkswagen's efforts to restore its credibility and accusing the company of impeding and obstructing regulators' inquiries and providing misleading information (Davenport & Hakim 2016). Back in December 2015, Volkswagen characterized its emissions scandal as a "chain of mistakes" which is a gross understatement. The company has equipped a staggering 11 million diesel cars since the 2009 model year with software called a "defeat device" used to cheat on emissions tests; when not being tested, the cars emit up to 40 times the allowable levels of nitrogen oxide pollution (Singh 2015). This emissions scandal is a disturbing case of systematic corporate fraud that has harmed customers, governments, and the health and well-being of citizens in the societies in which Volkswagen has been given the license to operate (Merrill-Sands & Du 2016; Boudette 2016; Singh 2015).

On April 22th 2016, VW took a €16.2 billion ($18.28 billion) charge related to the emissions-cheating scandal, forcing it to slash its 2015 dividends and post a deep loss. They reported a net loss of €1.58 billion for 2015, compared with a net profit of €10.85 billion a year earlier. They also reported an operating loss of €4.1 billion for the year. Revenue rose from 5.4% to €213.3 billion from €202.5 billion (Sloat 2016).

The €16.2 billion in charges compare with a previous figure of €6.7 billion that Volkswagen had set aside to cover recalls and repairs of vehicles affected by the emissions scandal. That figure was widely expected to balloon as the scandal spread and a person familiar with the matter said that the figure would enter double digits.

Volkswagen said the €16.2 billion charge covers buybacks, repairs, and legal costs to date. They agreed on the outlines of a plan to settle some legal claims in the United States which

would include giving owners of about 500,000 affected vehicles the option of selling the cars back to the company or having them repaired (Sloat 2016; Davenport & Hakim 2016; Singh 2015).

The media, journals, and magazines such as Fortune, New York Times, and Wall Street Journal are agreeing that VW will hardly recover and the future of the Brand is in doubt. The Company must ensure that this type of activity cannot take place again and through multiple communication channels, from official statements to advertising campaigns, continue to emphasize the brand's green credentials and commitment to mitigating the effect of the industry on the environment.

The prior example represents palpable cases on how companies' reputation and business integrity were ruin due to the careless on ethical and environmental matters. Volkswagen gives us a blunt lesson on how businesses should not approach social responsibility and sustainability. Hoodwinking stakeholders by paying empty talk and treating sustainability as a disguise is never going to deliver true value neither for the company nor for society. Indeed, as we have seen, it engenders significant costs (Du et al. 2010). Research shows that business value is created when social responsibility and sustainability are embedded in the company's culture and core business strategies (Boons et al. 2013; Schaltegger & Wagner 2011b).

When done right, companies benefit from a more favorable corporate image, greater customer loyalty, higher employee morale, and enhanced organizational learning and core competence (Du et al. 2007; Ethical Consumer Report 2012). And, in turn, societies benefit from harnessing the power and resources of corporations to address pressing social and environmental challenges (Merril-Sands 2016).

In contrast, to what some skeptics may think, sustainability issues are here to stay. It has gained strength and now it occupies an important place not only in the agendas of large organizations but also in national strategies on different countries around the world (Rachel & François 2016; Lucas et al. 2016). For example, last 11-20 July 2016, it took place the high-level Political Forum on Sustainable Development at New York City which is United Nations Central Platform for the follow-up and review of the 2030 Agenda for Sustainable Development and the Sustainable Development Goals, adopted at the United Nations Sustainable Development Summit on 25 September 2015 (United Nations Media 2016).

According to Ambassador Oh Joon interview, the Forum, which adopts a Ministerial Declaration, is expected to provide political leadership, guidance, and recommendations on the 2030 Agenda's implementation and follow-up; keep track of progress of the SDGs; spur coherent policies informed by evidence, science and country experiences; and also address new and emerging issues (Sambira 2016).

1.2 Research Background

Given the pressure on companies to embrace sustainability both internally and in their supply networks, it is not surprising that sustainability has received increasing attention

from different management disciplines (Zhu et al. 2008; Carter et al. 2015; Gimenez et al. 2012). Research in the domain of Sustainable Supply Chain has tackled several themes such as the drivers and barriers that face companies' engagement in sustainability (Walker et al. 2008; Sroufe & Nirenburg 2014; Foerstl et al. 2015; Large & Gimenez Thomsen 2011), and implementing various concepts and practices related to sustainability such as green purchasing (Zontangos & Anderson 2004), ethical sourcing (Goebel et al. 2012), and reverse logistics (Roach 2012). However, the integration of sustainability with supply chain analytics that incorporate disruptive technologies such as big data and predictive analytics is a complex process because companies are struggling with how to ensure the quality of their data, how to analyze it, and how to make practical and sustainable use of what they learn from it (Lisa & Toby 2017; Rogers Dale 2017). Sustainable Supply Chain Analytics (SSCA) is defined as the use of business analytics in the collection, analysis, and dissemination of sustainability-related data (Firouzeh et al. 2017). The goal is to provide the appropriate information that can be used for effective and efficient decision-making on sustainability issues (Deloitte 2013). A considerable amount of research has reported the need by organizations to manage and collaborate closely with suppliers and customers on sustainability issues (Leppelt et al. 2013) to achieve better control of risks and organizational sustainability (Foerstl et al. 2010; Wu et al. 2015). To this end, SSCA can gather and analyze sustainability-related data efficiently and effectively, thus supporting a variety of informational needs that include forecasting, analysis, and evaluation of economic, environmental, and social issues. Organizations need to develop and acquire capabilities to enable SSCA. Therefore, scholars and practitioners recognize that SSCA requires broader thinking and alignment between strategic goals and big data analytics as well as supporting organizational culture.

Additionally, practitioners and scholars are wondering how BDPA impacts the three sustainability aspects (environmental, economic, and social) in Supply Chain. BDPA becomes a competitive necessity for the management of supply chains with practitioners and scholars focused almost entirely on how BDPA is used to increase just the economic measures of performance (Chen et al. 2012). Later, (Wang et al. 2016) brought the term Sustainable Supply Chain Analytics (SSCA) to combine the techniques of BDPA applied to Sustainable Supply Chain. He defined SSCA to the use of methodologies and techniques to collect, analyze, disseminate, and use sustainability-related information for both strategy and operations. However, there is a limited understanding of the role of BDPA on SSCA and for this reason, it was chosen for this study. This thesis addresses this gap in the identification of dominant enablers to implement SSCA through a structured remote questionnaire and a case study. Later, it will proceed to analyze the data using exploratory factor analysis (EFA).

1.3 Outline of the Thesis

This thesis is composed of six chapters grouped into four parts as illustrated in Figure 1. The purpose of each chapter is described briefly below.

Chapter One discusses the introduction of Big Data and Predictive Analytics (BDPA) that become crucial for managing supply chain functions. BDPA has emerged as both a strategic and operational tool that may bring fundamental changes to the sustainable supply chain analytics (SSCA).

Chapter Two discusses the literature on Sustainability, Supply Chain Management, Supply Chain Analytics, the Internal/External enablers of SSCM, Big Data and Predictive Analytics. This chapter introduces sustainability as a concept and lays the ground for understanding what sustainability is and its importance to the industry. The second part in chapter two is dedicated to discussing the integration of sustainability with Supply Chain, Big Data and Predictive Analytics and the main concepts that are used to implement these practices within companies.

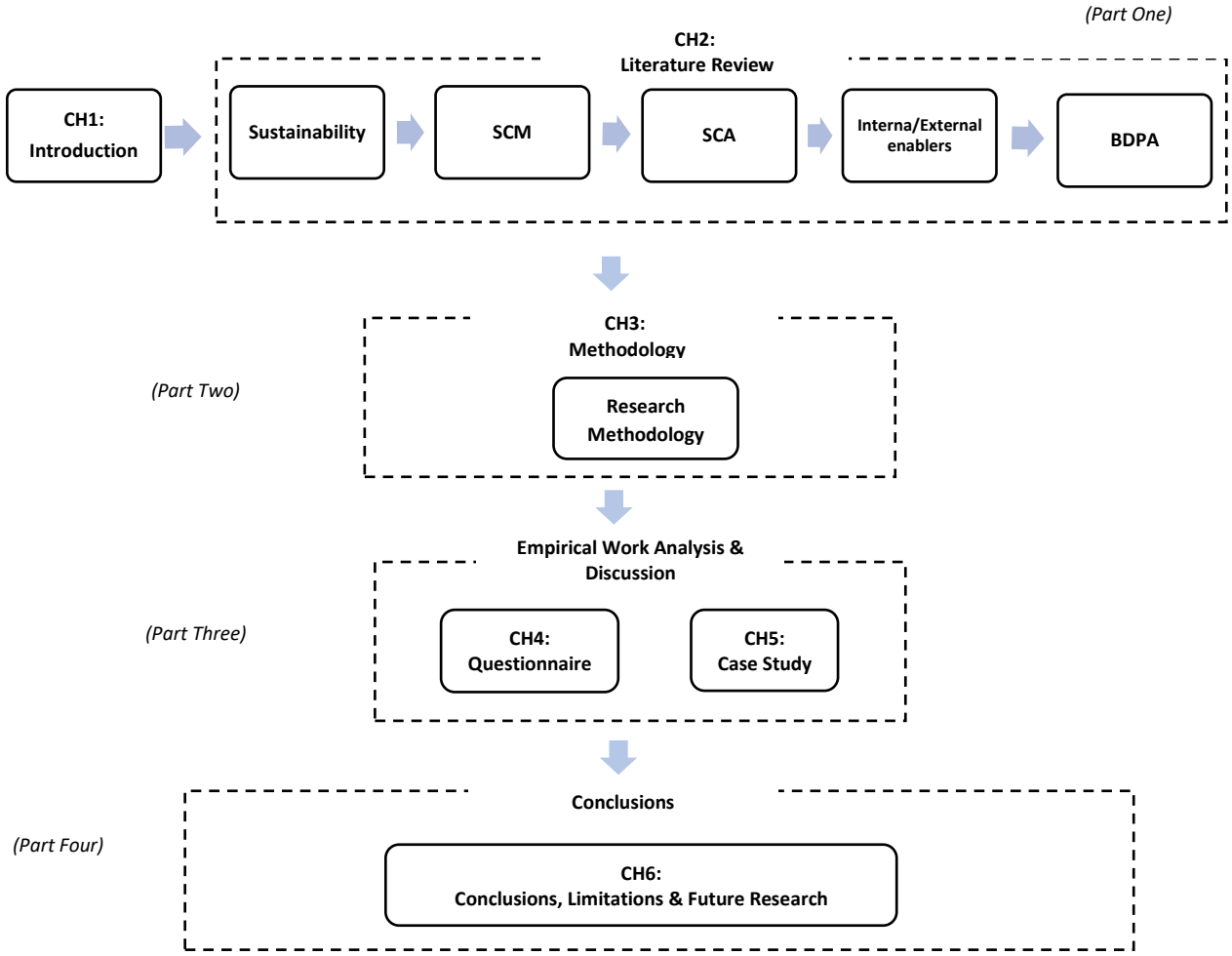
Chapter Three will provide an overview of the different methodologies and theories that can be applied in the field of sustainable supply chain. The aim of this section is to contribute to the methodological domain.

Chapter Four shows the data collection followed by the analysis and discussions of the results. The data were analyzed with Exploratory Factor Analysis using "R" software based on the answers obtained from the questionnaire developed on Google Forms.

Chapter Five provides a case study analysis. The case study is analyzed based on the datasets of five years from the mechanic department of "THE COMPANY A". The analysis process is done in accordance with the research questions and conceptual framework.

Chapter Six concludes the thesis by discussing and wrapping up the research findings around the research question and discussion from previous chapters. The findings from this thesis are discussed comparing the existing literature on enablers of SSCA to identify the contribution of the thesis to the existing literature. Some methodological and managerial implications are provided based on the findings and analysis. The chapter ends with enhancing the limitations of the thesis and suggesting avenues for future research.

Figure 1: Thesis Outline and Structure. Source: Author



1.4 Conclusions

This first introductory chapter provides the reader with a general overview of the thesis by identifying and describing the research gaps in the literature related to how the enabler/factors of big data and predictive analytics impact sustainable supply chain and briefly outlining the methodology used to conduct this research. The outline of the thesis and structure provides the connections between the chapters with short descriptions of the purpose of each chapter. This will make it easy for the reader to know the purpose of each chapter in advance before going through the whole thesis. The next chapter will introduce the literature review and the main concepts developed for the integration with SCM, Sustainability, Big Data, and Predictive Analytics.

Chapter Two: Literature Review

2.1 Sustainability and the Triple Bottom Line (3BL): *Is there a Difference?*

The term "sustainability" is not new as it has been used in the last three decades as an umbrella to address the need to pay attention to environmental and social issues and at the same time achieving economic prosperity. The terminologies of "*sustainability*" and "*3BL*" are used interchangeably in the literature to refer to the three pillars of environment, social and economic. The existence of several terminologies and various definitions for each terminology is confusing and raises the need to have a consensus on concrete terminology and definition (Andersen and Skjoett-Larsen 2009). The following subsections provide definitions and discussions to the two terminologies to clarify if there are differences between them.

2.1.1 Triple Bottom Line (3BL)

3BL is a concept originated at the beginning of the 1990s and used extensively by large corporations as a tool to address not only financial performance but also their environmental and social performances (Hacking and Guthrie 2008). (John Elkington 1997) defined 3BL as "the principle of ensuring that our actions today do not limit the range of economic, social, and environmental options open to future generations." Accordingly, the 3BL concept is developed to consider the intersection and balance of the three dimensions: environment, social, and economic at a microeconomic level. The aim is to realize environmental and social performance improvement and at the same time achieve long-term economic benefits and competitive advantages (Prahalad and Rangaswami 2009). Therefore, the assumption for 3BL is based on the company performing well in all three dimensions and reporting on its performance. 3BL reporting is used to define "company's ultimate worth in financial, social, and environmental terms" (Norman and Macdonald 2004). However, 3BL is criticized for being more of an accounting tool and overlooking the perspective of the supply chain when considering the three dimensions (Pagell and Wu 2009).

2.1.2 Sustainability

Sustainability holds several meanings and interpretations. The sustainability word can be understood as the capacity to maintain or to endure and adapt (Starik and Kanashiro 2013). Sustainability is a relatively new research topic, and it has gained momentum and wide consideration from the public and private sectors during the last decade. Most of the research refers to the Brundtland Report (World Commission on Environment and Development 1987) as the reference point and alleges for the wide consideration of sustainability especially from the industry. The report and its most quoted definition have induced wide reflections on sustainability applicability regarding the scope (environment, economic, and social) and scale (local, national, or international). Nonetheless, the sustainability definition provided in the report has been criticized for being generic and it provides little guidance for companies on how to link sustainability to their activities (Bansal 2005; Carter et al. 2015). This comes from the fact that the Brundtland report aims

for a global level implementation making the applicability of the definition at a micro-scale irrational (Carter & Rogers 2008; Jennings & Zandbergen 1995; Bartlett et al. 2007). Most importantly, the definition poses a question on how to operationalize sustainability in companies' activities and supply chains (Linton et al. 2007; Hutchins & Sutherland 2008; Vachon & Mao 2008).

2.1.3 Comparison

From the above discussion, it can be concluded that the two terminologies are used to address the three pillars: social, environmental, and economic. However, they have some differences in terms of applicability and how they are adopted by companies. 3BL is more financially oriented and has the reputation of being used as an accounting tool (Pagell & Wu 2009) to link and measure the performance of companies according to the three dimensions: social, environmental, and economic.

Although sustainability, as defined by the Brundtland report, is addressed at a general level, the implementation of sustainability by industry has evolved to encompass the environmental and social dimensions in addition to focusing on achieving economic advantages (Ahi & Searcy 2015). For example, (Hassini et al. 2012) define business sustainability as "the ability to conduct business with a long-term goal of maintaining the well-being of the economy, environment, and society". The interest of business in sustainability and its integration with companies' supply chains has operationalized the sustainability concept. SCM can be defined as ''the systemic, strategic coordination of the traditional business functions and the tactics across these business functions within a particular company 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'' (Mentzer et al. 2001). Based on this definition, integrating sustainability with SCM is challenging since the sustainability scope needs to encompass the individual companies and the whole supply chain. However, the integration of sustainability with SCM has led to many concepts in both the environmental and social dimensions (Srivastava 2007; Anne Touboulic 2015; Govindan et al. 2014; Björklund & Forslund 2013). Recently the concept of SSCM has emerged to encompass all the social, environmental, and economic pillars. Although there is no universal definition on SSCM, several definitions address clearly the importance of achieving the three pillars of sustainability (Craig & Dale 2008; Pagell & Shevchenko 2014) as it will be discussed later in this chapter.

Based on the above discussion on the two concepts, "sustainability" seems more appropriate to be adopted in this thesis as it is more associated with SCM and considers the three dimensions. However, this study will investigate what are the enablers of SSCA and what are the tools and techniques of BDPA that enable **social, economic, and environmental** performances through SCA. For this reason, I chose to work on this paper with the concept of "3BL" that considers the intersection and balance of the three dimensions of sustainability.

2.2 Companies Involvement in Sustainability

A great number of authors has been investigated the benefits that companies may gain from engaging in sustainability especially the ones that are related to environmental improvement (Corbett & Klassen 2006). Attempts have been made to show the link between the social and environmental improvements and their effects on improving economic performance (Benjamin T Hazen et al. 2016; Anne Touboulic 2015). The results vary where some researchers point out a positive link between the improvements in social or environmental dimensions and economic performance. For example, (Mollenkopf et al. 2005) show the potential cost savings that companies may obtain when they adopt activities related to recycling and reusing of packaging materials. (Gimenez et al. 2012) indicate in their study that environmental programs can lead to improvement in the performance of the three sustainability dimensions. Similarly, (Rao & Holt 2005) indicate in their survey on green supply chain management practices in South East Asia that green practices can lead to improvement in companies' competitiveness and economic performance. (Porter and van der Linde 1995) argue that environmental regulations may trigger innovation and lower the cost of products. The study findings of Geffen and Rothenberg (2000) indicate that environmental regulation for VOC emission was the main driver for automotive industries in the USA to improve their environmental performance.

On the social side, improving the working conditions of employees may enhance their motivation to improve productivity or develop innovative products. (Pagell & WU 2009) examine the practices of ten (10) exemplars in sustainability and show that the commitment of companies to sustainability can lead to a committed workforce that may result in enhanced innovation and better employees' retention. However, in some situations, the benefits may not accrue immediately from initiating environmental improvement. (Johnson et al. 1997) find out short-term benefits from sustainable supply activities may not be evident immediately and companies who are engaged in such practices may achieve that on a long-term basis.

Other studies indicate negative results or no connections between engaging in social or environmental initiatives and gaining economic or operational benefits (Zhu et al. 2008). Some initiatives are based on the acquisition of new technologies, equipment, or making radical changes to the already established operations. Under these conditions, achievements of environmental improvements are faced with high investment costs which may require a long time to be recovered. However, it is paramount for companies to know how to achieve the balance between the three pillars of sustainability in order to foresee the impact of their decisions and activities on each pillar (Hutchins & Sutherland 2008). (Pagell & WU 2009) in their study on best practices of SSCM for ten exemplary companies, they mention an example of a company that implemented a reverse supply chain to take back products after use and it was not efficient, also it was not well integrated with the forward supply chain. The reverse supply chain was costly to operate which affected negatively the economic performance of the companies. Although it offered an improvement to the environmental dimensions, some researchers state that sustainable supply chain activities that "well planned initiatives, which simultaneously take into

account the goals of social responsibility and firm performance, appear to result in improved financial performance" (Govindan et al. 2014; Nikolaou et al. 2011; Srivastava 2007).

Based on the above discussion, it appears that that engaging in sustainability is challenging and may not achieve the expected results. Companies may encounter obstacles during planning and implementation of sustainability initiatives which might lead to failure of the initiatives or getting different results from what they expect. Some of these obstacles are related to :

1. High cost of sustainability initiatives. Some sustainability projects require radical changes to be conducted such as adding new equipment, developing or modifying products to be sustainable which may require considerable start-up investments, training of the company staff, or an increase in the purchasing cost of environmentally friendly materials (Min and Galle, 2001). The long-term perspective needs to be considered in order to anticipate the benefits of sustainability activities such as sustainable supply chain analytics practices (Firouzeh et al. 2017).
2. Uncertainty in the benefits. The actual benefits from the sustainability initiatives could be less than what the company has initially anticipated (Murillo-Luna et al. 2011). For example, the lack of customer demand for sustainable products (Seuring & Muller 2008) may hinder the company's attempt to raise the prices of its sustainable products. In other cases, the benefits from the sustainability initiatives are difficult to quantify or measure due to lack of having proper measurement systems (Hervani et al. 2005).
3. Inertia within the company. This represents changing the existing investment, systems, and habits at the company (Velazquez et al. 2005). It is a vital factor for the successful implementation of sustainability projects (Ceschin 2013). The involvement and coordination of the sustainability projects among several departments within the company is a difficult task (Gibbs 2003).
4. Difficulty of involving partners. Companies have to spend considerable efforts and resources on engaging their partners such as suppliers, in sustainability activities, and convincing them about the benefits of sustainability. It is essential to unify the different objectives and goals of several suppliers to be in line with the company's sustainability objectives (Hassini et al. 2012).
5. Lack of transparency and information sharing. Transparency represents the visibility of information and its extent of availability to companies (Dubey et al. 2017; Awaysheh & Klassen 2010). Information sharing between companies and their partners in the supply chain such as suppliers requires the availability of trust between the actors. In some situations, the company or suppliers refrain from exchanging information for the fear of leaking vital information to competitors (Daudi et al. 2016; Belkadi & Bernard 2008; Gibbs 2003). The information

asymmetry may prevent companies from truly reaping the benefits of improving their sustainability performance (Bai et al. 2012; Sarkis et al. 2011).

The next section provides a discussion on the three pillars of sustainability and how they are approached by companies internally and within their supply chains.

2.3 Sustainable Supply Chain Pillars: The 3BL

2.3.1 Economic

The main objective of companies is to make money and generate profits. Even for non-profit organizations, money is essential for them to continue operating. The economic performance represents the ability of companies to offer returns to its shareholders. The economic pillar within sustainability in the existing literature is generally better understood. (Carter & Rogers 2008) argue that developing social and environmental knowledge and resources is difficult to imitate. (Rao & Holt 2005) indicate that green supply chains of companies lead to improvement in their competitiveness and economic performance. As stressed by (Pagell & WU 2009), sustainability initiatives of companies should take into consideration the three pillars of sustainability to avoid trade-off situations. From the sustainability point of view, companies should seek activities that generate profits and long-term competitiveness. However, it is not uncommon to find trade-offs between the three pillars of sustainability as improving one pillar may cause an adverse effect on the other pillars. Thus, the interaction of the three pillars should be considered (Anne Touboulic 2015; Winter & Knemeyer 2013).

2.3.2 Social

Although the focus on the environment has dominated the studies on sustainability in SCM (Ashby et al. 2012; Lee et al. 2014; Vachon & Klassen 2006a), there is an increasing trend in considering the social dimension of sustainability. (Awaysheh & Klassen 2010) identify social practices as those management practices that affect the development of humans and protect people. The improvement in the social pillar represents an opportunity for companies to improve their relationships with communities, shareholders, employees, and customers (Carter & Easton 2011; Carter & Jennings 2002). Companies can gain several advantages from improving their social performance such as minimizing the risk of being exposed to media and enhancing companies' image and reputation avoiding implementing activities that cause harm to the society or preventing improper practices of suppliers such as using child labor, low wages, and unsafe working conditions (Ahi & Searcy 2015; Klassen & Vereecke 2012). In addition, improvement in safety, health, and working conditions may lead to improvements in employees' productivity and innovation.

Companies attempt to extend the concern over social issues into their supply chains. This requires the focal companies to assess their suppliers to make sure that the actors in the supply chains are not abused and making enough earnings to continue and survive (Pagell & WU 2009). Codes of conduct have been used often by companies to address their social concerns and set the criteria for their suppliers to implement and comply with their principles. Codes of conduct may include local and international laws and standards that

companies expect their suppliers to fully comply with. In some cases, companies may use what is called model codes of conduct where companies provide guidelines to their suppliers and allow them to devise their own codes of conduct (Awaysheh & Klassen 2010; Andersen & Skjoett-Larsen 2009). Codes of conduct can be utilized as a tool to communicate a message to the stakeholders and society that the company is concerned with sustainability and it is committed toward achieving social and ethical standards. On the other hand, codes of conduct can be exploited by companies to promote a green and ethical behavior while their actual behavior is different than the announced one. On this green-washing behavior, companies seek to gain benefits such as increasing their stock price, image improvement in the market and attracting more customers.

2.3.3 Environmental

The environmental pillar in sustainability has received a lot of attention in the literature (Klassen & Vereecke 2012) where the general aim in this pillar is to identify the interaction of companies with the natural environment. The concern over environmental issues, such as resource depletion, pollution, climate change, ozone layer depletion, and waste management, has escalated the governmental and business attentions toward protecting the environment (Góncz et al. 2007). The environmental pillar in sustainability means that companies should consider their activities' impact on the environment and include these considerations in their daily activities and operations. A core issue in this sustainability pillar is the conservation of natural resources and the rate of depletion. The companies' consumption rate of resources such as energy and materials should be lower than the rate of natural reproduction. This is essential to achieve the principle of sustainable development as "living on this planet as if we intended to go on living here forever" (Porritt 2012). Based on this, targeted contributions were highlighted by the derivation of one of the research questions of this study: *How the use of certain tools and techniques of BDPA impacts the effectiveness of decision-making on sustainable supply chain analytics performances*? Below in Table 1, there is a brief description of the major management systems, concepts, and tools that are often used by companies to improve their environmental decision-making.

Table 1: Initiatives for Implementing Sustainability (Meqdadi 2015). Scope nomenclature: social (Sl), environmental (Evt), and economic (Ec).

Tools	Definition/Descriptions	Scope (3BL)		
		Ec	Evt	Sl
Carbon Disclosure Project (CDP)	It is a non-profit organization that provides environmental information such as greenhouse gas (GHG) emissions related to companies and cities.		x	
Carbon Footprint	The total amount of GHG emissions caused by a product or company during a defined period. It expresses as ton of CO2.		x	
Closed-loop supply Chain	"The design, control, and operation of a system to maximize value creation over the entire life cycle of a product with a dynamic recovery of value from different types and volumes of return over time"		x	x
Code of Conduct	A document contains the set of rules, principles, and practices that companies aim to address their concerns over sustainability/CSR.	x	x	
Dow Jones Sustainability Index (DJSI)	DJSI is regarded as one of the world's foremost sustainability indices. DJSI benchmarks the sustainability performances of leading companies based on indicators for their environmental, social, and economic performance. (http://www.sustainability-indices.com/).	x	x	x
Global Reporting	A not-for-profit organization that aims to promote companies reporting	x	x	x

Initiative (GRI)	on their sustainability activities. GRI developed a sustainability reporting framework that contains reporting guidelines and principles for companies to report on their social, environmental, and economic performance. (www.globalreporting.org)			
Green Purchasing/sustainable procurement	"The set of purchasing policies held, actions taken, and relationships formed in response to concern associated with the natural environment. These concerns relate to the acquisition of raw materials, including supplier selection, evaluation, and development: suppliers, operations: in-bound distribution, packaging, recycling, reuse, resource reduction, and final disposal of the firm's products" (Bobis & Staniszewski 2009; Meehan & Bryde 2011; Zsidisin & Hendrick 1998a).		x	x
Green Supply Chain Management	"Supply management activities that are attempts to improve the environmental performance of purchased inputs, or the suppliers that provide them" (Jabbour 2015).		x	x
ISO 14001	An international standard that sets the criteria for companies in establishing an environmental management system and certifying it (www.iso.org/fr/iso-14001-environmental-management.html).		x	
Leadership in Energy and Environmental Design (LEED)	LEED is a 3rd party that certifies the design, construction, and operation of buildings that are environmentally compatible; they provide a healthy work environment and are profitable. https://new.usgbc.org/leed		x	x
Life-Cycle	LCA is a tool used to assess the		x	

Analysis (LCA)	environmental impact of a product from cradle-to-grave. There is a dedicated journal to LCA (The International Journal of Life Cycle Assessment). https://www.netl.doe.gov/research/energy-analysis/life-cycle-analysis			
OHSAS 18001	OHSAS 18001 is an international occupational health and safety management system. It aims to help companies to control occupational health and safety risks. https://www.iso.org/iso-45001-occupational-health-and-safety.html	x	x	
Product Stewardship	An approach that aims to consider the impact of a product through all its life cycle stages till its end of life. (http://productstewardship.net/about/what-product-stewardship)		x	
Purchasing Social Responsibility	"Purchasing activities that meet the ethical and discretionary responsibilities expected by society" (Carter & Jennings 2002; Craig & Dale 2008).	x		
Registration, Evaluation, and Authorization of Chemicals (REACH)	REACH is a regulation of the European Union, adopted to improve the protection of human health and the environment from the risks that can be posed by chemicals while enhancing the competitiveness of the EU chemicals industry. It also promotes alternative methods for the hazard assessment of substances in order to reduce the number of tests on animals. (http://ec.europa.eu/enterprise/sectors/chemicals/reach).		x	
Reverse Logistics	"The process of planning, implementing and controlling the efficient, cost-effective flow of raw materials, in-process inventory,		x	x

	finished goods, and related information from the point of consumption to the point of origin for the purpose of recapturing or creation value or proper disposal" (Tibben-Lembke & Rogers 2002)			
SA 8000	A social certification standard based on the UN ILO declaration of human rights. SA 8000 aims to empower and protect all personnel within an organization's control and influence who provide products or services for that organization including personnel employed by the organization itself and by its suppliers, subcontractors, sub-suppliers and home workers. (www.sa- intl.org).	x		
World Business Council for Sustainable Development (WBCSD)	The WBCSD is a CEO-led organization of forward-thinking companies that galvanizes the global business community to create a sustainable future for business, society, and the environment. WBCSD sets with its member initiatives and programs to improve sustainability. (http://www.wbcsd.org).	x	x	x
World Resource Institute (WRI)	WRI is a non-governmental organization that seeks to create equity and prosperity through sustainable natural resource management. WRI focuses on six areas: climate, energy, food, forests, water, and cities and transport. (http://www.wri.org).		x	x

2.4 Innovation

The domain of innovation offers new opportunities to create competitive advantages. Within the last few years, the concept of innovation built as an advantageous and critical

stream of research (Baregheh et al. 2009). Notwithstanding, the high level of attention and acceptance of innovation has been the cause of much debate. There are many definitions of innovation out there. One of the most important came from Joseph Schumpeter, 1934 in which he differentiates between *"inventions"* and *"innovations".* An **invention** is an idea that might be used in production; while **innovation** is doing things differently (Schumpeter 1934). This last consideration had led him to another suggestion, namely, the "*creative destruction"* (Schumpeter 1942), by which he describes the *"process of industrial mutation that incessantly revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one."* On the other hand, The Oslo Manual (OECD & Eurostat 2005) defines innovation as: *"The implementation of a new or significantly improved product (good or service) or process, a new marketing method, or a new organizational method in business practices, workplace organization or external relations*." What is noteworthy in this description is that there is a focus on technology, marketing, and commercial success. Based on this definition, certain non-commercial institutions such as hospitals or universities are not able to engage as much in the innovation process. Similarly, (Humbert 1995) mentioned that innovation is considered a major driver of competitiveness. They defined it as the following :

1. Renewals and enlargements of the range of products and services and the associated markets;
2. Adoption of new methods of production, supply, and distribution;
3. The introduction of changes in work organization, the working conditions, and skills of the workforce, etc.

An interesting definition was also given by (Crossan & Apaydin 2010). That one indicates that despite the intricacy and disjunction of innovation research, categorizations for innovations are classified as innovation as a process and innovation as an outcome.

2.4.1 Innovation as a Process

The topic of innovation flows in different directions. Some authors analyzed the topic as a *process* that should answer the question of "***how"*** (Bello et al. 2004; Perdomo-Ortiz et al. 2006; Crossan & Apaydin 2010; Assink 2006; Zimmermann et al. 2016). Here innovation was conceived as a process where researchers tried to understand how it emerges, develops, and becomes a part of the routine activities of an organization (Damanpour & Gopalakrishnan 1998). Because of that, reviews suggest that the innovation process depends on several factors that address the question "how." Dimensions that cope strictly with this question are *drivers* and *source.* Both can be either internal or external. For example, an internal driver can be resources and knowledge, while an external driver would be an imposed regulation or a market opportunity.

With regards to the processes and aims of innovation, (Jorna 2006) has several observations:

- Many innovations are long-term activities.

- Innovations are not guaranteed to succeed.
- Traditional discussions about innovation are often one-dimensional, tending to refer only to material aspects.
- The importance of technology in innovation is strongly over-estimated
- Innovation is tied to knowledge: innovation starts with knowledge; it elaborates that knowledge or generates new knowledge and produces knowledge as the outcome. Thus, knowledge is the engine of innovation.
- Individuals rarely realize innovations. Even the brightest inventor needs other people to work out details and to conduct tests and case studies, as well as to convince others that the innovation is as brilliant as the inventor thinks it is.

In summary, innovations take time, there is no guarantee of success, and there is currently too little focus on services and organizational forms. Moreover, innovation is not just a scientific exercise, but that in principles it is about knowledge with people as the carriers of this knowledge. So, innovation will succeed only if people cooperate. According to all the positions mentioned above that effectively describe innovation, sustainable innovation will be explained in the following sections.

2.4.2 Innovation as an Outcome

As outlined above, the concept of *"innovation"* also describes the result of a process (Garcia & Calantone 2002). Some authors analyzed the topic as an outcome that should answer the question "what." Dimensions that deal precisely with this question are *referent, object, magnitude.* The ***referent*** dimension grounds the criterion which defines the *newness* of innovation as an outcome such as new to the firm, new to the market, new to the customer or the industry (Tushman & Anderson 1986; Garcia & Calantone 2002; Novak & Eppinger 2001; Davila et al. 2005). According to (Garcia & Calantone 2002), the criterion of newness demonstrates that innovations involve the following four aspects:

- **Sciences/technology:** as well as the state of the knowledge in physics and the behavioral sciences. In other words, it refers to changes in technological principles (e.g. predictive analytics and big data) embedded in innovation (Danneels et al. 2001; Garcia & Calantone 2002; Gemünden et al. 2007). This aspect can take either a micro/macro perspective.
- **Organizational:** aspect assesses the changes that are required within a company to accommodate and innovate. As a result, this aspect measures how well the organization's capabilities manage innovation and the changes related to the product, the service or the process and the structure itself (Faber et al. 2005; Danneels et al. 2001; Kock et al. 2011). This aspect is limited to the microsphere because it refers just to a company-wide level.

- **Environmental/social:** This aspect takes macro-sphere because it refers to changes that innovations may produce in a company's environment (Gemünden et al. 2007), such as suppliers and competitors. In this aspect, behavioral and attitudinal changes of individuals outside the firm as well as regulatory and infrastructure changes (Hartmann 2014).

- **Market:** aspects refer to an alteration of the benefits of innovation as perceived by other companies, consumers, and customers (Garcia & Calantone 2002; Faber et al. 2005; Hartmann 2014). This aspect can take either a micro/macro perspective.

The ***object*** dimension also is known to some researchers as a *"form"*. It differentiates in the following typologies (Assink 2006; Crossan & Apaydin 2010; Neely et al. 2001): **product or service innovation, process innovation, business model innovation, and organizational innovation**. Regarding ***magnitude***, this indicates the degree of newness. Usually, academics differentiate among incremental/continuous and radical/disruptive innovation (Christensen 1997; Gopalakrishnan & Damanpour 1997). **Incremental/continuous innovation** concerns an existing product, service, process, or method whose performance has been significantly enhanced, improved, or upgraded in an existing market or organization. **Radical/disruptive innovation** is when something is completely new and will lead to a completely new infrastructure. Radical/disruptive innovation commonly has a significant impact on all four aspects mentioned before and on the economic activity of businesses as well (Garcia & Calantone 2002; Tushman & Anderson 1986; Christensen 1997; Chase 2016; Assink 2006; Danneels et al. 2001; Freeman 1984).

2.4.3 Sustainable Innovations

(René Jorna 2006) believes that sustainability in the environmental sense is always directly or indirectly connected to the way in which people possess and organize knowledge. In general, managing and making this knowledge operational takes place to organizations, firms, enterprises, and institutes. Innovation can mean that something already in existence is renounced or abandoned and something new replaces it. As well as products, services, and organizations themselves can be innovated; a good innovation always means that, within a certain context, knowledge has been created (Faber et al. 2005). Sustainable innovation is accomplished by knowledge creation, and the ways and structures that embed this knowledge in organizations need to be analyzed and stimulated (Morioka et al. 2016). A proper innovation process results in making knowledge sustainable. The essence of sustainable innovation is shaped by a process perspective on sustainability (Jorna 2006). Whenever someone says that a particular product, production process, or service is sustainable, it means that a balance has been achieved between the three pillars of sustainability, where "Planet" is often the key pillar (Faber et al. 2005). They mentioned that it is hard to measure the degree of sustainability of an enterprise or innovation as these change over time. They, therefore, suggest transforming the term "sustainability" to "making sustainable". By making something "sustainable" they want to raise the issue that

the organizational processes in the organizations are constantly changing (René Jorna 2006). The same goes for innovation. An innovation is not there for a limited period after finishing. Innovations endure as processes rather than projects. However, in the innovation process, there has to be a constant focus on sustainability (René Jorna 2006). Consequently, from the perspective of the human and organizational sciences, design rules have to be formulated and implemented such that the innovation process can sustain itself (Faber et al. 2005).

2.4.4 Cutting Edge New Technologies: Big Data and Predictive Analytics.

As part of this analysis, this study will explore two of the emerging technologies that are driving major innovation and represent potential changes in the sustainable supply chain design. Those technologies are big data and predictive analytics and it will be discussing in the next section.

2.5 Big Data and Predictive Analytics

As part of this analysis, this study explores emerging technologies that are driving major innovation and represent potential changes in the sustainable supply chain analytics design. This technology is big data and predictive analytics (BDPA). There is no clear consensus on different terminologies related to big data in the literature. However, there is a pattern of evolution regarding the definitions and development of capabilities from different perspectives and authors as you will see in Table 2 below:

Table 2: Big Data definitions and perspectives

Authors	Definitions	Focus
(Fosso Wamba et al. 2015; Gunasekaran et al. 2017)	"a holistic approach to manage, process, and analyze data regarding high volume, variety, velocity, veracity, and value to create actionable insights for sustained value, delivery, measuring performance, and establishing competitive advantages."	Informatics perspectives
(Beyer & Laney 2012)	"High-volume, velocity, and variety information assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision making."	Informatics perspectives
(Brown et al. 2011)	"Big data refers to datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze."	Informatics perspectives
(Hurwitz et al. 2013)	''The capability to manage and analyze petabytes of data. It enables companies to deal with clusters of information that could have an impact on the business."	Capability perspectives

(Wang et al. 2015)	‘‘The ability to acquire, store, process, and analyze a large amount of health data in various forms and deliver meaningful information to users that allow them to discover business values and insights in a timely fashion.”	Information life cycle management
(Hofmann 2017)	“The ability of the organizations to process the volume of data integrated from a variety of data sources at a high velocity.”	Capability perspectives
(Richey et al. 2016a)	‘‘The ability of organizations to collect and organize supply chain data from heterogeneous systems distributed across organizational boundaries, analyze it either batch-wise or real-time or near real-time and visualize it intuitively to create proactive supply chain system and support decision making.”	Supply Chain Perspectives

As you can see in the table above, there are many definitions from different perspectives. For example, in the informatics perspective they focus more on the information assets such as velocity, volume, variety etc. to enhance the decision making inside firms as we can see in the definition given by (Beyer & Laney 2012): *“High-volume, velocity, and variety information assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision making.”* On the other hand, in the capability perspective, the authors paid more attention in the ability that the companies have to analyze and use the data that they extract with BDPA such as the following definition: *“The ability of the organizations to process the volume of data integrated from a variety of data sources at a high velocity.”* (Hofmann 2017). Even though *all these definitions are valid*, the definition that fits with this work is the following: *“The ability of organizations to collect and organize supply chain data from heterogeneous systems distributed across organizational boundaries, analyze it either batch-wise or real-time or*

near real-time and visualize it intuitively to create proactive supply chain system and support decision making" (Richey et al. 2016a).

Based on the nature of data, Big Data (BD) was characterized mainly by three dimensions (3V's) 'Volume,' 'Velocity', and 'Variety' (IBM 2015; Brown et al. 2011; Sonka 2014; Gunasekaran et al. 2016). But, apart from the 3V's Big Data can also be characterized by another two dimensions 'Veracity' and 'Value' as given in Table 3 below:

Table 3: The 5V's of Big Data

Dimensions	Indicator/Units	Descriptions	Authors
Volume	GBytes or Tbytes	Volume refers to the magnitude of data generated. Big data implies enormous volumes of data. It used to be employees created data. Now, that data is generated by machines, networks, and human interaction on systems like social media. The volume of data to be analyzed is massive.	(IBM 2015; Brown et al. 2011; Sonka 2014; Wamba et al. 2017; Fosso Wamba et al. 2015; Davenport et al. 2006)
Veracity	% of data declared "outlier," deviation from mean, % of missing values	Veracity refers to ensuring data quality, verifying unreliable, and uncertain data. It is the data that is being stored and mined meaningful to the problem being analyzed.	(IBM 2015; Mishra et al. 2016; Brown et al. 2011; Neaga et al. 2015; Ge & Jackson 2014; Davenport et al. 2006)
Velocity	GBytes per second or minute or delta T	Velocity refers to the speed at which data is generated. It deals with the pace at which data flows in from sources	(IBM 2015; Brown et al. 2011; Sonka 2014; Wamba et al. 2017; Fosso Wamba et al. 2015;

		like business processes, machines, networks, and human interaction with things like social media, sites, mobile devices, etc. The flow of data is massive and continuous.	Davenport et al. 2006)
Variety	# of variables, # of sources, # of formats	Variety refers to "structural heterogeneity in a dataset." Strictly speaking, in the many sources and types of data, both structured and unstructured. We used to store data from sources like spreadsheets and databases. Now, data comes in the form of emails, photos, videos, monitoring devices, PDFs, audio, etc. This variety of unstructured data creates problems for storage, mining, and analyzing data.	(IBM 2015; Brown et al. 2011; Sonka 2014; Wamba et al. 2017; Fosso Wamba et al. 2015; Davenport et al. 2006)
Value	ROI	The extent to which big data generates economical and worthy insights and/or benefits through extraction and transformation.	(IBM 2015; Mishra et al. 2016; Brown et al. 2011; Neaga et al. 2015; Ge & Jackson 2014; Shacklett 2017)

2.5.1 The value of using Big Data and Predictive Analytics (BDPA)

According to McKinsey and Company, big data and predictive analytics (BDPA) would be an opportunity to knuckle down some challenges that the industry is facing. For example, improve customer experience, making sense of large amounts of unused business data, improve inaccurate or misleading revenue forecasts and models, focus on micro-decisions, etc. (Court 2015). This consultancy firm found that collecting, storing, and mining BDPA for insights can create significant value for the world economy, enhancing the productivity and competitiveness of companies and the public sector, and creating a substantial economic surplus for consumers (Manyika et al. 2013; Brown et al. 2011). Due to the perceived benefits of BDPA, organizations are highly motivated to develop their technical and organizational capabilities to extract value from data. The core aspects of generating value depend on the organization's ability to capture, store, and analyze a large volume of complex data generated in real or near real-time with the support of advanced analytics (Yesudas et al. 2014). Further, recent studies show that supply chains are gathering huge amounts of data, but companies and practitioners are facing extreme difficulties in understanding the required capabilities to transform data into value (Lisa & Toby 2017; Rogers Dale 2017; Richey et al. 2016b). For example, a survey was conducted in June 2017 via an e-mail invitation to readers of CSCMP's Supply Chain Quarterly and subscribers to a newsletter produced by Competitive Insights. According to (Rogers Dale 2017), from Arizona State University, explaining his findings regarding the knowledge of practitioners in big data, he said:

"We found a lot of confusion, there's not a unified understanding of the concept, and there's not a clear direction of how you should go. What most companies are doing is they are managing big data analysis with Excel spreadsheets."

Also, some researchers mentioned that big data and predictive analytics could improve the ability to help sourcing decisions and reduce environmental footprint (Mark van Rijmenam 2014; Fawcett & Waller 2014). Indeed, there are some authors that are saying that it is time to move forward in how BDPA can be used to enhance operational and economic-based supply chain outcomes. So, we should examine how BDPA can increase measures of the other two 3BL aspects of the supply chain that are becoming increasingly important in today's global market place (Benjamin T Hazen et al. 2016).

2.5.2 BDPA Untapped Potential

So far, most of the excitement about disruptive technologies such as BDPA in the industries has centered on marketing and sales. For example, for the food industry, health industry, and retail industry, the opportunities begin higher upstream and end lower downstream. At the upstream end, for example, in the food industry, the agricultural practices followed by dairy farmers, cacao and coffee producers, wheat and barley producers, cattle farmers, and so on result in enormous variations in commodity costs in an industry where raw materials represent easily 60 percent of the cost of goods sold

(COGS) (Magnin 2016): In Table 4 you can see the opportunities and challenges of the industry in general and how BDPA can help and create values in the given examples.

Table 4: Big data and predictive analytics (BDPA) value chain opportunities (Magnin 2016; Manyika et al. 2013; Brown et al. 2011; Court 2015).

Opportunity	Industry Challenge	How BDPA can help and create value (examples)
Win the innovation game	• High need for innovation, particularly in inputs for increase speed	• Holistic input optimization. • Building a "data innovation engine" using insights from millions of trials to find the "product per profit & loss".
Optimize Operations	• Improve performances forecasting and production optimization.	• Real-Time production optimization with analytics tools that help producers and retailers to optimize resource allocation and prices by using scalable compute technologies to determine optimum commodity pricing.
Increase supply chain transparency	• Currently little foresight into high product volumes. • High price volatility	• Increasing forecasting accuracy with real-time data collection and analysis. • Integrated planning across the value chain for lowering response times, risks.
Step up downstream operations	• Processing high volume, huge business with low	• "Operations big-data toolbox" production optimization, e.g.,

	operational efficiency	holistic, simulation-based plant optimization, predictive maintenance.
Tackle the infrastructure challenge	• Poor infrastructure in emerging markets, particularly LATAM and Africa.	• Advanced analytics to identify key bottlenecks in infrastructure (e.g., car/trucks monitoring) • Infrastructure network optimization, e.g., warehouse location based on geospatial data/models.
Anticipate waste	• Enormous amounts of residential waste.	• Granular data collection of waste streams in households, etc., as a basis for, e.g. • Changed offerings in retail. • Regulation and public services.

2.6 Sustainable Supply Chain Management (SSCM)

There is a growing need for integrating sustainability sound choices into supply-chain management. There are early links that were fueled by the desire to optimize economic performance, indicating the introduction of the environmental aspect even in the initial stages of SCM. The idea grew into green supply chain management (GSCM) (Sarkis 2003) and culminated in sustainable supply chain management (SSCM) (Seuring & Muller 2008). There is a comprehensive literature review on SSCM by (Craig & Dale 2008; Seuring & Muller 2008) that contains 191 papers in English, peer-reviewed journals between the years 1997 and 2007 showing a considerable number of publications for the later years. This number has risen to > 300 in the year 2011 (Seuring 2013; Beske & Seuring 2014) showing that SSCM is currently a thriving field of academic research. At this point, I will skip repeating definitions of SCM that can be found in some contributions already made by (Mentzer et al. 2001). In supply chain management literature, the inclusion of sustainability is most often based on the triple bottom line

(3BL) approach which calls for equal consideration of all three pillars of sustainability, namely economy, ecology, and society. (J. Elkington 1997; Seuring & Muller 2008; Seuring et al. 2008) define SSCM: “As the management of material, information, and capital flow, as well as cooperation among companies along the supply chain, while taking goals from all three dimensions of sustainable development, into account which are derived from customer and stakeholder requirements.” As mentioned before, to meet the requirement of sustainability practices in the supply chain, a company must be able to comply with the 3BL. In Table 6, below there is a compilation of the meaningful sustainable supply chain 3BL dimensions, metrics, and factors that are often used by companies to improve their SSC processes.

Companies in the manufacturing and service industries have witnessed dramatic changes in terms of how companies conduct their activities and operations. Internationalization of companies and global sourcing, rapid technology development, and shorter product life cycle (Hutchins & Sutherland 2008; Vermeulen & Seuring 2009) are some of the most influencing factors that force companies to restructure their organizations and supply chains. Under these operating conditions, companies’ supply chains increasingly reach several geographical areas, and this poses risks to companies on how to take care of their activities’ impact on sustainability. Although supply chains are effectively structured to achieve economic and competitive advantages, they are often sourcing of sustainability risk. For example, sourcing from low-cost countries can achieve economic benefits but the transfer of goods to Europe and the USA may increase CO2 emission and energy consumption (Abbasi & Nilsson 2012). In addition, companies must avoid social and ethical issues in such regions to protect their brands' image and reputation. Therefore, the scope of companies’ sustainability implementation has been extended to include the upstream and downstream activities in their supply chains. This has implications that companies are responsible for their suppliers’ activities' impact on sustainability as well as the product through its life cycle till its final disposal (Ashby et al. 2012; Awaysheh & Klassen 2010; Rao & Holt 2005; Seuring & Müller 2008). As mentioned by (Carter & Easton 2011) “the broad concept of sustainability, and the key interfaces that sustainability has with supply chain management, strongly suggests that sustainability is instead license to do business in the twenty-first century. And supply chain management is an integral component of this license.”

Literature indicates that sustainability improvement needs concerted efforts and synergies between companies and their supply chain partners such as suppliers since companies cannot achieve that alone (Andersen & Skjoett-Larsen 2009; Rao & Holt 2005). In fact, a considerable environmental risk can be passed on to companies by their suppliers which may jeopardize their environmental performance and reputation (Petersen et al. 2005). As (Halldorsson et al. 2007) point out, sustainability is no longer within the company’s domain but expanded to encompass all activities along the supply chain. (Teuteberg & Wittstruck 2010) indicate in their study that cooperation with partners is a key factor for

successful SSCM. (Andersen & Skjoett-Larsen 2009) concluded in their study on IKEA's case that practicing sustainability in the supply chain requires companies to make consideration of sustainability internally as well as with their suppliers. Therefore, initiatives launched by companies for sustainability improvement need synergy and cooperation with suppliers (Darnall et al. 2008).

From the above discussion, it can be concluded that attaining improvement in sustainability cannot take place without the involvement of partners in the supply chain. This is the premise for the convergence of SCM with sustainability and the development of several concepts and approaches to improve sustainability within supply chains. The main merit of this convergence is the consideration of sustainability issues such as the environment beyond companies' confined boundaries. This wider scope offers a possibility to consider the various actors' activities along the upstream and downstream of the supply chain. Such consideration requires an extension of SCM scope to include activities such as product design, recycling, re-manufacturing or disposition of product at the end of its life (Linton et al., 2007). Although there is a growing interest in the SCM community in the subject of sustainability, a considerable portion of the current studies focuses on specific parts of the supply chain or claims of studying sustainability while focusing just on one pillar of sustainability (Carter and Rogers, 2008; Pagell and Wu, 2009). It is also noticeable that research on sustainability is dominated by studies on the environment while little focus is paid to the social dimension (Ashby et al., 2012; Carter and Easton, 2011; Gimenez and Tachizawa, 2012; Klassen and Vereecke, 2012; Seuring and Müller, 2008b; Vachon and Mao, 2008).

The various concepts mentioned in Table 1, Initiatives for Implementing Sustainability, have focused on one or two pillars of sustainability. For example, reverse logistics, closed-loop supply chain, green purchasing, and green supply chain management focus on the environmental improvement in the supply chain while the concepts of purchasing social responsibility, logistics social responsibility, and ethical sourcing consider the social issues from the purchasing perspective. The concept of SSCM has emerged to encompass all these concepts, provide consideration to the three pillars simultaneously and at the same time consider the entirety of the supply chain when implementing sustainability. The idea behind SSCM is that the performance of the supply chain should consider in addition to the economic performance, the impacts of supply chain activities on the environmental and social systems. Due to the lack of universally accepted definition on SSCM, several definitions have been provided by different authors as shown in Table 5 below.

Table 5: Supply Chain Managements Definitions. Scope nomenclature: social (Sl), environmental (Evt), and economic (Ec).

Authors	SSCM Definitions	Scope			Focus
		Sl	Evt	Ec	
(Carter & Rogers 2008)	The strategic, transparent integration and achievement of an organization's social, environmental and economic goals in the systemic coordination of key inter-organizational business processes for improving the long-term economic performance of the individual and its supply chain.	x	x	x	• Organization • Supply Chain
(Ciliberti et al. 2010a)	The management of supply chains where all the three dimensions of sustainability, namely the economic, environmental, and social ones, are taken into account.	x	x	x	• Supply Chain
(Pagell & WU 2009)	The one that performs well on both traditional measures of profit and loss as well as on an expanded conceptualization of performance that includes social and natural dimensions.	x	x	x	• Supply Chain
(Seuring & Muller 2008)	Management of material, information and capital flows as well as cooperation among companies along supply chain while taking goals from all three dimensions of sustainable development, i.e.,	x	x	x	• Companies • Supply Chain • Customers • Stakeholders

	economic, environmental and social, into account which are derived from customer and stakeholder requirements".				
(Hassini et al. 2012)	The management of supply chain operations, resources, information, and funds in order to maximize the supply chain profitability while at the same time minimizing the environmental impacts and maximizing the social well-being	x	x	x	• Supply Chain
(Pagell & Shevchenko 2014)	The designing, organizing, coordinating, and controlling of supply chains to become truly sustainable with the minimum expectation of a truly sustainable supply chain being to maintain economic viability, while doing no harm to social or environmental systems	x	x	x	• Supply Chain

Table 6: Sustainable supply chain 3BL dimensions (Beske & Seuring 2014; Erol et al. 2011; Zhao et al. 2017)

Dimensions	Metrics	Factor	Indicator	Literature
Economic	1. ROI 2. Customer service 3. Delivery performance 4. Supply link 5. Order planning 6. Production evaluation 7. Costs	1. Revenue, profits 2. Process and query time 3. Flexibility, order fulfillment 4. Supplier evaluation, supply capacity 5. Order entry lead time 6. Scheduling, Capacity	-customer service cost (order processing time, customer orders per hour) - Inventory carrying cost (fill rate%, forecast accuracy %)	(Boons et al. 2013; Erol et al. 2011; Carter &Easton 2011; Sikdar 2003; Veleva &

		7. Logistics, supply, inventory	-procurement cost (purchase orders per hour, supplier lead time) -transportation costs (perfect documentation%, on-time%) -warehousing costs (shipping accuracy% inventory accuracy%) -total logistics cost (perfect order %)	Ellenbecker 2001; J. Elkington 1997; Adams 2006; Zhang 2011; Rey-Marston 2014).
Environmental	1. Pollution controlling 2. Emission preventing (done) 3. Waste processing 4. Legislation 5. Policy	1. Water, air 2. Gas, fluid, chemical 3. Waste-reducing, recycling, reusing 4. Act on environment protection 5. Public pressure on the environment 6. Energy	-Annual water consumption m3/m2a -Annual energy consumption kW h/(m2 a) -Waste minimization (recycling rates) kg/(m2 a)	(Seuring & Muller 2008; Morioka et al. 2016; Delmas & Blass 2010; J. Elkington 1997; Adams 2006; Erol et al. 2011; Zhang 2011; Zhao et al. 2017).
Social	1. Customer benefits 2. Ethics/Moral 3. Equity	1. Service level, satisfaction, flexibility. 2. For public	-Average annual training time per employee, h/a	(Russo & Mariani 2013; Du et

	4. Trust 5. Safety 6. Public benefits 7. Reputation	health, safety, transparency 3. Income, political, economic, social fairness 4. Interpersonal trust, brand trust. 5. Product safety, consumer safety 6. Welfare, training, work conditions, quality of life 7. Code of conduct, brand name	-Annual personnel turnover -Gender diversity -Effectiveness of compensation - The fraction of total sales invested in social projects per year. -Effectiveness of performances management system	al. 2010; Marshall et al. 2015; J. Elkington 1997; Adams 2006; Erol et al. 2011; Zhang 2011).

2.7 Sustainable Supply Chain Analytics (SSCA)

2.7.1 Why analytics in supply chain management?

According to (Souza 2014; Firouzeh et al. 2017), the supply chain for a product is the network of firms and facilities involved in the transformation process from raw materials to a product and in the distribution of that product to customers. In a supply chain, there are physical, financial, and informational flows among different firms. Supply chain analytics focuses on the use of information and analytical tools to make better decisions regarding material flows in the supply chain. In other words, supply chain analytics focuses on analytical approaches to make decisions that better match supply and demand. Well-planned and implemented decisions contribute directly to the bottom line by lowering sourcing, transportation, storage, stockout, and disposal costs. As a result, analytics has historically played a significant role in supply chain management, starting with military operations during and after World War II, particularly with the development of the simplex method for solving linear programming by George Dantzig in 1947. Supply chain analytics became more ingrained in decision making with the advent of enterprise resource planning (ERPs) systems in the 1990s and more recently with **"Big Data"** applications, particularly in descriptive and predictive analytics, as it will be described with some examples in this research.

Supply-Chain Council (SCC) is an independent non-profit organization. As the cross-industry standard for supply chain management, SCC has developed and endorsed the

Supply-Chain Operations Reference (SCOR)-model, a process reference model for supply chain management. The (SCOR)-model provides a good framework for classifying the analytics applications in supply chain management. The (SCOR)-model outlines four domains of supply chain activities: ***source, make, deliver, and return.*** A fifth domain of the SCOR model ***'plan'*** is behind all four activity domains. Furthermore, a key input of the supply chain planning process is demand forecasting at all time frames: long, mid, and short term with planning horizons of years, months, and days, respectively. Table 7 illustrates different decisions in each of the four SCOR domains that can be aided by analytics. These decisions are further classified into strategic, tactical, and operational according to their time frame (Supply Chain Council 2018).

Table 7: SCOR model and examples of decisions at the three levels SCOR (Supply Chain Council 2018)

SCOR DOMAIN	SOURCE	MAKE	DELIVER	RETURN
Activities	Order and receive materials and products.	Schedule and manufacture, repair, remanufacture or recycle materials	Receive, schedule, pick, pack, and ship orders.	Request, approve and determine the disposal of products and assets
Strategic	• Strategic sourcing. • Supply chain mapping	• Location of plants. • Product line mix at plants.	• Location of distribution centers. • Fleet planning	• Location of return centers
Tactical	• Tactical sourcing • Supply chain contracts	Product line rationalization. Sales and operations planning.	• Transportation and distribution planning. • Inventory policies at locations.	• Reverse distribution plan
Operational	• Material requirement planning and inventory replenishme	• Workforce scheduling. • Manufacturing, order tracking, and	• Vehicle routing (for deliveries)	• Vehicle routing (for returns collection)

	nt orders.	scheduling.		
Plan	Demand forecasting (long term, midterm, and short term)			

Table 8: Analytic techniques used in supply chain management (Firouzeh et al. 2017; Souza 2014)

Analytics Techniques	Source	Make	Deliver	Return
Descriptive	• Supply Chain Mapping	• Supply Chain Visualization		
Predictive	• Time-series methods (e.g. moving average, exponential smoothing, autoregressive models). • Linear, non-linear, and logistics regression. • Data-mining techniques (e.g., cluster analysis, market basket analysis)			
Prescriptive	• Analytic hierarchy process. • Game theory (e.g., auction design, contract design)	• Mixed-integer linear programming (MILP) • Non-linear programming	• Network flow algorithms. • MILP • Stochastics dynamic programming	

2.7.2 Analytics Techniques in SCA

Analytics techniques can be categorized into three types: descriptive, predictive, and prescriptive. **Descriptive analytics** derives information from significant amounts of data and answers the question of what is happening. Real-time information about the location and quantities of goods in the supply chain provides managers with tools to adjust delivery schedules, place replenishment orders, place emergency orders, change transportation modes, and so forth. Traditional data sources include global positioning system (GPS) data on the location of trucks and ships that contain inventories, radio frequency identification (RFID) data originating from passive tags embedded in pallets

(even at the product level), and transactions involving barcodes. Information is derived from the vast amounts of data collected from these sources through data visualization, often with the help of geospatial mapping systems. RFID is a significant improvement over barcodes because it does not require a direct line of sight. Accurate inventory records are critical in supply chains as they trigger regular replenishment orders and emergency orders when inventory levels are too low. Although RFID technology helps in significantly reducing the frequency of manual inventory reviews, such reviews are still needed because of data inaccuracy due to, for example, inventory deterioration or damage or even tag-reading errors. **Predictive analytics** in supply chains derives demand forecasts from past data and answers the question of what will be happening. **Prescriptive analytics** derives decision recommendations based on descriptive and predictive analytics models and mathematical optimization models. It answers the question of what should be happening. Agreeably, the bulk of academic research, software, and practitioner activity in supply chain analytics focus on prescriptive analytics. In Table 8, it has been provided a summary of analytics techniques descriptive, predictive, and prescriptive used in supply chains in terms of the four SCOR domains of source, make, deliver, and return.

Based on the literature review and analysis, in this section, it has been outlining popular techniques for supply chain analytics (SCA). As the central component of SCA, advanced analytics techniques are the basis for the success of supply chain strategies implementation, and daily operations for every business organization.

2.7.2.1 Statistical Analysis

According to (Wang et al. 2016), statistical techniques include two types of techniques: qualitative and quantitative. Qualitative methods, based on the subjective judgment of consumers or experts, are appropriate when past data are not available. Quantitative approaches are used to make predictions as a function of past data. Both methods are applied to short or intermediate-range decisions. Two widely used quantitative techniques in SCA are time series analysis and forecasting and regression analysis. Time series analysis analyses data to extract meaningful patterns and statistics. Time series forecasting 'predicts' the future based on historically observed data. Regression analysis helps in understanding relationships and causality effects between variables. Big data, as mentioned before, is characterized by velocity, volume, and variety, which leads to the following challenges to Business Analytics (BA) (Fan et al. 2014): (a) volume accumulates data noise, and incidental homogeneity; (b) high volume creates high computational costs and algorithmic instability; (c) high variety requires different techniques and methodologies. These challenges result in heterogeneity, experimental variations, and statistical biases. Hence, more adaptive and robust procedures are required because traditional statistical methods were designed for moderate sample sizes and low-

dimensional data, but not for massive data. Due to Big Data features, effective statistical procedures have received increasing attention for exploring.

2.7.2.2 Simulation

Big data (BD) brings more challenges to modeling and simulation (Sanyal and New, 2013; Parashar, 2014). Firstly, depending on reductionism and causality, the basic simulation theory cannot meet the demand of processing Big Data on the supply chain, although it predefines concepts such as target, boundary, entity, constraints, among others. Secondly, BD makes modeling methods difficult to perform well and requires new types of models because of more complex problems and a large amount of computation. However, modeling and simulation can benefit from BD (Belaud et al., 2014; Pijanowski et al., 2014). Supply chain analytics (SCA) offers more in-depth analysis and processing, and new methods for the simulation problems with massive amounts of data. Moreover, SCA makes it possible for modeling and simulating complex systems as it focuses on the interrelationship between supply chain operations and emphasizes the analysis of integral data associated with supply chain integration. SCA can aggregate disintegrated data from different supply chain operations and achieve global optimization (Ranjan, 2014).

2.7.2.3 Optimization

The use of optimization techniques as part of SCA helps to improve the accuracy of forecasting demand and supply chain planning while creating challenges that relate for instance, on applying penalized quasi-likelihood estimators on high-dimensional data which create large-scale optimization problems (Slavakis et al., 2014). BD optimization is not only expensive and unstable but presents slow convergence rates, thus making traditional techniques difficult to succeed in SCA. To deal with the massive size of BD, hence, it is necessary to implement large-scale non-smooth optimization procedures, develop randomized, approximation algorithms and parallel computing-based methods, and to simplify implementations (Fan et al., 2014). Conversely, optimization techniques are suitable for data analysis in supply chain management. Optimization helps analyze highly complex dynamic systems with huge data volumes, multiple constraints, and factors, and it can gain insights that allow individuals to make appropriate decisions. In addition, optimization helps to analyze the measures of supply chain performance such as cost reduction and demand fulfillment, among others. Another benefit associated with optimization is its flexibility because it can uncover new data connections, turn them into insights, and unlock more business values from huge amounts of data (Balaraj, 2013).

2.7.3 Sustainable SCA

Sustainable Supply Chain Analytics (SSCA) is described as the use of business analytics in the collection, analysis, and circulation of sustainability-related data. The objective is to

line the opportune information that can be used for effective and efficient decision-making on sustainability issues (Deloitte 2013). The literature has high pointed the need by organizations to manage and collaborate closely with suppliers and customers on sustainability concerns (Leppelt et al. 2013) to accomplish better control of risks and organizational sustainability (Foerstl et al. 2010; Paulraj 2011). For this purpose, Supply Chain Analytics (SCA) can gather and analyze sustainability-related data efficiently and effectively, thus supporting a variety of informational needs that include forecasting, analysis, and evaluation of economic, environmental, and social issues. Organizations need to develop and acquire capabilities to enable sustainable SCA. Therefore, we do recognize that sustainable SCA requires broader thinking and alignment between strategic goals and big data analytics as well as supporting organizational culture (Richardson 2011; Ransbotham 2017; Wang et al. 2016). Scholars have enhanced the relationship between strategic goals, culture, transparency, and risk management as the building blocks of sustainable SCA (Ageron, Blandine; Lavastre, Olivier; Spalanzani 2013; Mello & Stank 2005; Gunasekaran & Spalanzani 2012). To enable this relationship, BDPA and SSCA come to the foreground to secure the collection, cleansing, analysis, and distribution of information seamlessly across functions and processes (IBM 2018). It is important that leaders understand the role of SSCA to build the format needed for taking strategic decisions related to sustainability. This will enable leaders to acquire the appropriate analytical capabilities as well as the appropriate resources needed on adopting SSCA to create organizational value through the fulfillment of the organizational goals (Bertels 2010; Deloitte 2012). Top and senior management commitment is a priority for those organizations and supply chains that are embracing sustainable practices (Foerstl et al. 2015; Gattiker & Carter 2010).

2.8 Factors and Enablers for implementing sustainable supply chain analytics

2.8.1 Introduction

A key challenge for companies operating in global sustainable supply chains is the balance between achieving a competitive advantage and acting sustainably while fulfilling their different stakeholders' expectations to preserve reputation, legitimation, and credibility. Companies face a strong reputational risk of negative public perception by important stakeholders such as regulators, customers, shareholders, media, and non-governmental organizations (NGOs) (Pedersen 2009; Ciliberti et al. 2010b). Furthermore, focal companies are generally held responsible for their suppliers (Seuring & Muller 2008). However, social and environmental issues constitute operational risk, including inconsistent and poor product quality or supply chain disruptions (Zsidisin 2003; Lee & Klassen 2008). As a result, sustainability issues along the supply chain might lead to a decrease in financial performance (Siltaoja 2014) or a loss of competitiveness (Sajjad et al. 2015). This risk-oriented strategic

approach to manage sustainability along supply chain processes is affected through supplier evaluation, whereas a focus on supplier development seeks to develop a business case from sustainable supply chain policy implementation (Harms et al. 2013).

Thus, former research has found that the strategic approaches of companies focus either on managing supply chains to create sustainable products or on managing the supplier base to diminish risks and ensure performance (Seuring & Muller 2008).

Therefore, sustainable supply chain analytics (SSCA) has become a salient issue in recent research. SSCA combines the concepts of supply chain management and sustainability (Turker & Altuntas 2014) and entails all activities of companies to increase the sustainability of their supply chains (Pagell & Wu 2009) with the characteristics of Big Data Analytics. As mentioned before in the section "Sustainable SCA", researchers have already identified several drivers and barriers to the successful implementation of SSCA (Diabat et al. 2014; Oelze 2017). However, there is no research completed that seeks to identify the influence degree of each factor for facilitating/delaying sustainability adoption (Wang et al. 2016; Firouzeh et al. 2017). This research aims to follow the advice of other scholars in estimating the impact factor of enablers/disruptions using big data and predictive analytics on SSCA.

2.8.2 Enablers of Sustainable SCA

The ***enablers*** of SSCA (Walker et al. 2008; Lin et al. 2010)***:*** are the factors that motivate the adoption of sustainable supply chain analytics. These enablers are described for any innovation explained before as well as for SSCA. For this reason, they have been included in the conceptual framework. The present study focuses on analyzing the enablers for SSCA adoption from environmental, economic, and social perspectives. This research sought a fit for sustainable adoption of the traditional supply chain by using the terms "sustainable supply chain management: enablers for green supply chain and supply chain innovation." The identified enablers are shown in Table 3 and Table 4 respectively. I have to point out that in the original papers, there were 25 enablers and they were focused on the green supply chain. On the other hand, for this study, it has been used eleven significant (11) enablers. These enablers were divided into two groups external/internal, as you'll see below.

2.8.3 Internal Enablers

A requisite for fruitful implementation of SSCA standards is the compliance of the company's employees. Scholars frequently are mentioning the commitment of the top management, but also their involvement and specific support as being beneficial (Oelze 2017). In the same manner, an overall supportive culture for sustainability, the existence of an environmental mission, and the history of an organization are acknowledged enablers for SSCA. These include the involvement of employees.

Additionally, state of the art brought us strategic aspects. Thus, the existence of a sustainability strategy for supply chain analytics and its alignment with the overall corporate strategy has been identified as crucial (Dey et al. 2011; Hervani et al. 2005). The basic strategic planning

of the implementation of SSC policies has already been recognized as conducive to their successful implementation (Klimley 2007). Further, strategic supplier collaboration has been defined as the "collaborative paradigm" that is essential to achieve a competitive advantage through sustainable supply chain analytics (Firouzeh et al. 2017; Mani et al. 2017; Wang et al. 2016).

Furthermore, previous research enhances the resources and expertise of companies in the context of enablers for SSC. More specifically, the availability of resources and the overall size of a company constitute enablers for SSC since they determine the possible sustainability effort of a firm (Alvarez et al. 2010). Besides, the existence or development of capabilities related to sustainability and general supply chain are highlighted in the academic literature (Large & Gimenez Thomsen 2011). In particular, this relates to the training of people within the purchasing department (Andersen & Skjoett-Larsen 2009). Moreover, prior studies suggest evidence for well-performing operational metrics as an enabler for SSC (Sikdar 2003; Clift 2003). In Table 9, you will see the internal enablers related to the top management and the methodology used by each author to reach their studies.

Table 9: Internal Enablers for the Sustainable Supply Chain Analytics adoption (Walker et al. 2008; Lin et al. 2010; Oelze 2017; Diabat et al. 2014)

No.	Internal Enablers: Top management related	Research methodology used by the authors
1	Skillful policy entrepreneurs	Qualitative/Interview
2	Values of owner	Case study/participation
3	Involvement of employees	Survey/questionnaire
4	Reduction of costs	Case study/interviews
5	Pressure of Investor	Case study
6	Quality Improvement	Survey/questionnaire

2.8.4 External Enablers

External enablers are firmly related to the global context in which a firm works. On this point, the national culture of a supplier can constitute an enabling factor for SSCA (Ciliberti et al. 2010a). Moreover, a technological and logistical integration of supply chain members and information sharing are conducive to successful implementation (Vachon & Klassen 2006a; Zsidisin & Hendrick 1998b). According to this, they can also reduce the need for audits through an enhanced understanding of suppliers' processes (Barratt 2004). However, SSCA is only supported when the relationship between the focal firm and its supply chain members is characterized by trust and transparency (Oelze et al. 2016; Ciliberti et al. 2010b). In this respect, long-term collaborative structures within but also outside the supply chain support SSCA. This applies in particular to collaboration within a sector with NGOs or with competitors (Pagell & Wu 2009; Oelze et al. 2016; Vachon & Klassen 2006b). In Table 10, you will see the external enablers related to the top management and the methodology used by each author to reach their studies.

Table 10: External Enablers for the Sustainable Supply Chain Analytics adoption with references.

No.	Related to:	External Enablers	Author	Research Methodology used by the authors
1	Competition	Improve firm SSCA performances	(Carter & Rogers 2008 ; Carter et al. 2007)	Survey/questionnaire
2	Regulations (e.g., ISO 14000 certification)	Adoption of health and safety standards	(Carter & Rogers 2008 ; Carter et al. 2007)	Survey/questionnaire
3	Society/Public pressures	Adoption of green practices	(Govindan 2013; Zhu et al. 2012 ; Nishat Faisal 2010)	Case study/interviews
4	Customer Satisfaction	Quality improvement	(Hendricks & Singhal 2005; Hussain 2011)	Case study/interviews

As you can see in both tables 9 and 10, I am including the author and the methodology used respectively. The readers may ask themselves, why is the research methodology important here? To start this research, it is needed to make a map of the existing internal/external enablers and get information on how the authors reach them. Additionally, this map can help me to know where exactly I am standing up and make

something different that may contribute to the field of study. At the same time, it can help me to decide which methodology I can use in this research. As I already mentioned previously in the introduction of this section, there is no research completed that seeks to identify the influence degree of each enabler for facilitating/delaying sustainability adoption. Companies are struggling with how to derive sustainable value from the supply chain data. Based on this, targeted contributions were highlighted by the derivation of two of the three research questions of this study: *1. How the influence degrees of certain enablers impact the effective implementation of BDPA on SSCA practices within companies? 2. How do internal practices compete with external pressure in the adoption of BDPA for SSCA policies and practices?* These questions will be explained with more details in the following sections.

2.13 Conclusions

This chapter discussed the literature review, identified research gaps, interaction approach, and the main concepts that are adopted for studying how the enablers of big data impact on sustainable supply chain analytics. The next chapter presents and discusses the research methodology, research questions, and conceptual framework that are applied in this thesis.

Chapter Three: Research Methodology

3.1 Organizational Theories and Methodologies on Sustainable Supply Chain.

3.1.1 Theory Building by Literature Review

(Kotzab Herbert, Seuring Stegan, Muller Martin 2005) in "Conducting a Literature Review—the example of Sustainability in Supply Chains" they present how a review gets-up-and-go in an ordered way. Assorted limitations had to be considered to cut down the number of papers studied to a reasonable and workable number. This prepares the terrain for organizing a content analysis where both quantitative and qualitative points of the body of research are determined.

They are the two main reasons why a literature review is considered by these authors as a fundamental part of the research process. One is because it helps to generate ideas and summarizes existing research, the other one is related to any contribution to research (Kotzab Herbert, Seuring Stegan, Muller Martin 2005).

Some authors defined literature review as: "a systematic, explicit, and reproducible method for identifying, evaluating, and interpreting the existing body of recorded work produced by researchers, scholars, and practitioners." In other words, it helps to identify the conceptual content of the field and can endow to theory development. As a result, content analysis can be used. According to Brewerton, Paul M., and Lynne J. Millward, "Organizational research methods: A guide for students and researchers." Sage, 2001, p.151; distinguish qualitative, quantitative, and structural content analysis which involves the development of a representation of the relationship between elements in the target material. In order to do this, both qualitative and quantitative aspects of the data have to be considered. These aspects are shown as a process model for content analysis by (Seuring & Muller 2008) and were made by the following steps below:

Material Collection: definition and delimitation of material to be collected and searched for relevant literature.

Descriptive Analysis: underlying features of the selected materials, just as: research methods, number of publications per year, etcetera. They are checked.

Category Selection: settlement of the top-drawer categories and dimensions to be used in arranging the compiled materials.

Material Evaluation: examination and categorization of the selected materials according to the picked basic categories and dimensions.

As I mentioned before, the literature review represents an important pillar in the research process. At the early stages of this thesis, the purpose of the literature review was to gain knowledge and insights on big data, sustainability, and predictive analytics

from the perspective of supply chains. The study begins with a literature review that you already saw in Chapter 1 to identify conceptual contributions in the field and seek an initial list of dimensions that will be needed for consideration in the development of the conceptual framework. At this early stage, for the critical review, the main resources to gather scientific knowledge were:

1. Hardcopy readings, which mean published books, references, magazines, etc., and

2. Online literature database of Ecole Centrale de Nantes, Audencia Business School, and different scientific online databases such as Google Scholars, Business Source Complete, Web of Sciences, and EBSCO Discovery Tool.

Afterward, a review of the following top journals was conducted:

- ✓ Logistics Research,
- ✓ Journal of Supply Chain Management,
- ✓ International Journal of Production Economics,
- ✓ Industrial Marketing Management,
- ✓ Journal of Product Innovation Management,
- ✓ Strategic Management Journal,
- ✓ Business Strategy and the Environment,
- ✓ Journal of Cleaner Production,
- ✓ Supply Chain Management: An International Journal, International Journal of Operation and Production Management,
- ✓ International Journal of Physical Distribution and Logistics Management,
- ✓ Journal of Engineering and Technology Management.

The review began with a search for each journal in the different scientific online databases that were mentioned before. Within each database, the keywords “sustainable supply chain,” “supply chain analytics,” “disruptive technologies,” “supply chain enablers” and “big data and predictive analytics” were searched for each journal. The articles were reviewed to ensure that they explicitly addressed sustainable supply management as well as sustainable supply chain analytics. This initial identification of articles generated inquiries that addressed the role of sustainable supply chain analytics in new product innovation and examined the role of various disruptive technologies such as Big Data and Predictive Analytics. In this way, the search process for articles was done in an eclectic way and resulting in papers that were more focused and relevant to the research topic. However, compared to on-line resources, the amount of researched materials from hardcopy publications was limited.

In the second step, the articles gathered from the first step were checked for their relevance to the thesis subject and irrelevant papers were excluded. Although this thesis is quantitative, papers with qualitative techniques were considered as well, especially

those that have relevant information to the thesis subject. Both paper types were included: the empirical and conceptual papers. During the stage of writing the thesis, the literature review continued where more articles were searched and reviewed. In addition to the journals, papers from conferences were also targeted such as IPSERA, IFAC and ICPR conferences. Many conference papers were found relevant to this thesis. The literature review also used books related to sustainability and Big Data in practice specifically books related to the interaction approach.

3.1.2 Surveys/Questionnaires

According to (Kotzab Herbert, Seuring Stegan, Muller Martin 2005) survey research plays a key role in many disciplines when it comes to collecting data. They explained that electing a survey strategy allows the collection of a large amount of data in an efficient manner. Regularly, this is done by using questionnaires in which researchers bring together standardized data that can be compared easily.

In the supply chain field, it seems that this methodology is very significant. (Kotzab Herbert, Seuring Stegan, Muller Martin 2005) cited a group of authors who show the popularity of the surveys in Logistics and Supply Chain Management.

Commonly, researchers use the self-administered postal or mail surveys as much as they provide inexpensive and easily administered results from many respondents. Despite using this method, it has disadvantages counting low return and high non-response rates due to a lack of external validity for samples and no control over the survey situation regarding the way the questionnaires are completed and how respondents are motivated to give their respective answers (D.B. Grant et al., 2005, p. 140).

3.1.3 Case Study as a Research Strategy

A case study has been advocated by many authors as a methodology to test, refine, or build theories (Stuart et al. 2002; Voss et al. 2002; George & Bennett 2005; Yin 2014; Eisenhardt 1989). A case study is a research strategy that can be used to understand the dynamics of a phenomenon in specified settings (Eisenhardt 1989). Case studies are likely to appear in formal research venues as journals and professional conferences, rather than popular works. The resulting body of 'case study research strategy' has had a prominent place in many disciplines and professions, ranging from psychology, anthropology, sociology, and political science to education, clinical science, social work, and administrative science (Yin 2014). It can be defined as *"a research method that involves investigating one or a small number of social entities or situations about which data are collected using multiple sources of data and developing a holistic description through an iterative research process"* (Carter & Easton 2011). According to (Seuring 2008), a case study has an empirical inquiry that:

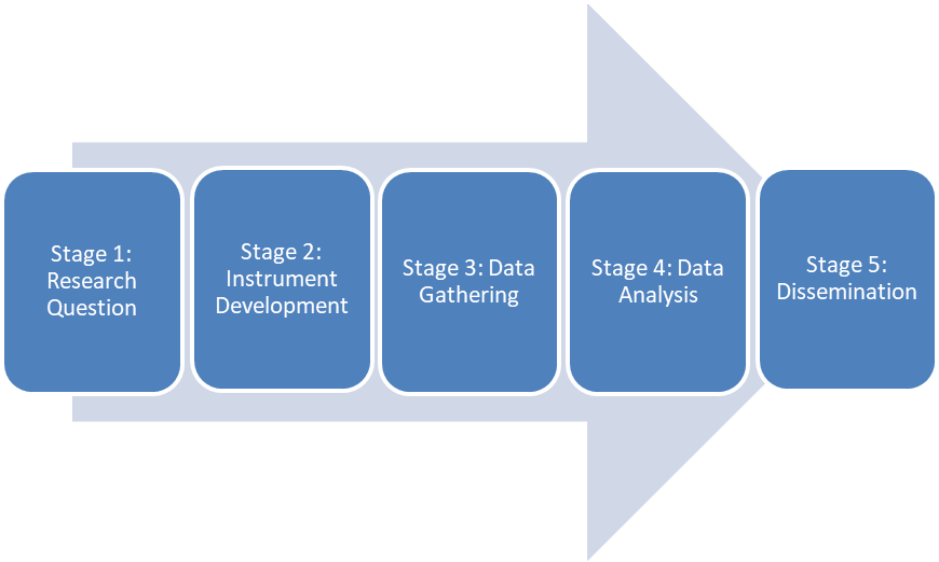
1. Investigates a contemporary phenomenon within its real-life context, especially when…

2. The boundaries between phenomenon and context are not clear.

This method enables researchers to answer **"how"** and **"why"** questions while considering how a phenomenon is influenced by the context within which it is situated. (Stuart et al. 2002) suggested that a case study is an appropriate research methodology to map the field of supply chain management. According to (Voss et al. 2002), the actual use of the case study methodology may facilitate current research on supply chain management for four major purposes: exploration, theory building, theory testing, and theory extension/refinement. (Yin 2014) mentioned that the research process for case studies is like those used for other research. (Stuart et al. 2002) proposed a five-research process showing in Figure 2.

It becomes more suitable when the individuals in the organizations under the study possess part of the whole picture or have different views about the studied phenomena making other methods such as surveys less suitable to gather these different perceptions (Johnston et al., 1999). In addition, a case study can be used to provide in-depth insights into the studied phenomenon where the **richness of data cannot be achieved through quantitative methods.**

Figure 2: The Five-Stage Research Process Model (Stuart et al., 2002)



3.1.4 Organizational Theories

Organizational theories are not easy to define. According to (Sarkis et al. 2011), organizational theories within business and management research have been influenced by a variety of other fields and disciplines including psychology, sociology, political science, engineering, and economics. This author defines organizational theory: "as a management insight that can help explain or describe organizational behaviors, designs,

or structures." Additionally, this author mentioned that organizational theories have introduced broad applications to several disciplines within management studies. The application of organizational theories to organizations and the natural environment as well as the supply chain separately is becoming more established.

A summary of the theories is provided in Table 11 below:

Table 11: Summary of Organizational Theories

Theories	General Conceptualisation
Complexity Theory	Complexity increases; firms find it more difficult to plan and predict their organizational actions, e.g., GSCM implementation. It is firm to be sensitive and responsive to their environments with co-evolution and interdependencies in adapting to the system (Crozier and Thoenig, 1976)
Ecological modernization (EMT)	As a systematic eco-innovation theory, an EMT is geared towards jointly achieving industrial development and environmental protection through innovation and technological development, or 'modernity' (Janicke, 2008; Murphy and Gouldson, 2000). At least two dimensions of an EMT can influence GSCM research and practice, new politics of pollution and technological innovation.
Game Theory	Mutual dependence and trust overcome member's temptation to pursue self-service behavior. (McCarter, M. W., & Northcraft, G. B., 2007).
Information Theory	Unequal environmental information exists between industry and customers. Managing under this information asymmetry environment may require 'signaling' and other information-theoretic approaches (Simpson et al., 2007)
Institutional Theory	Institutional theory examines how external pressures influence organizational actions (Hirsch, 1975). Within institutional theory, three forms of isomorphic drivers exist.

	Namely, coercive, normative, and mimetic (DiMaggio and Powell, 1983)
Resource-based view (RBV)	The resource-based model of competitive advantage suggests that competitive advantage may be sustained by harnessing resources that are valuable, rare, imperfectly imitable, and non-substitutable (Barney, 1991).
Resource Dependence Theory (RDT)	RDT suggests that, in the supply chain, member firms should depend and collaborate to seek higher performance gains in the long-run instead of pursuing short-term benefits at the expense of others. One important assumption of the RDT is that firms cannot be fully self-sufficient with regards to strategically critical resources for survival.
Social Network (SNT)	An SNT considers organizational outcomes as a function of the social relationships between organizations or individuals in an organization (Jones et al., 1997). An SNT has been described as having two major elements namely, density and centrality (Rowley, 1997).
Stakeholder Theory	Stakeholder theory suggests that companies produce externalities that affect many parties (stakeholders) which are both internal and external to the firm. Externalities often cause stakeholders to increase pressure on companies to reduce negative impacts and increase positive ones.
Transaction cost economics	Transaction cost economics focuses on how much effort and cost are required for two entities such as buyer and seller to complete an activity (economic exchange or transaction) (Williamson, 1981).
Diffusion of Innovation Theory (DoI)	It is the process by which an innovation is communicated over time among the participants in social systems. The four main elements influence the spread of a new idea: the innovation itself, communication

	channels, time, and a social system (Rogers 1995)

3.2 Theoretical Groundings

3.2.1 Dynamic Capabilities (DCs)

The dynamic capabilities framework was born out of the resource-based view of the firms (Grawe 2009). According to (Teece et al. 1997), dynamic capabilities (DCs) are "a subset of the competencies which allow the firm to create new products and processes and respond to changing market circumstances" (Teece 2007), explained that there are three types of managerial activities that can make dynamic capabilities as you will see in Table 12: sensing (which means identifying and assessing opportunities outside your company), seizing (mobilizing your resources to capture value from those opportunities), and transforming (continuous renewal).

The principal aim of the DCs approach is to construe the root of a company's advantage in a long-term perspective and to support managers in maintaining the company's success over time (Teece 2007). Moreover, there are several authors who have maintained the contribution of DCs to improve competitive advantages both directly and indirectly (Helfat & Peteraf 2009; Gebauer 2011). DCs have been used with different perspectives such as to analyze firms' international expansion (Al-Aali & Teece 2014) or to handle the challenge of the global market (Weerawardena et al. 2007). Other studies e.g. (di Stefano et al. 2010) distinguish dynamic capabilities by the type of knowledge they contain, e.g., (functional capabilities; integrative capabilities; innovation capability). Although, dynamic capability theory is well adapted to organizational innovation, not being specifically related to a single technology and it is easily related to the development of new processes, systems, and business models in which it seems to fail (Assink 2006). Comparatively, (Salunke et al. 2011) have specifically tested this model to innovation in service firms, (Ulusoy 2003) voiced some capabilities as an **enabling factor that could foment innovation**, by mentioning continuous improvement, learning, problem-solving, and product development. He presented DCs as a **moderator factor** on the relationship between the drivers to innovation and the implementation of different forms of innovation inside the company. In general terms, a **moderator factor** *is a qualitative (e.g., sex, race, age, class) or quantitative (e.g., level of reward) variable that affects the direction and* ***strength*** *of the relation between an independent variable and a dependent variable. Specifically, within a correlational analysis framework, a* ***moderator*** *is a third variable that affects the zero-order correlation between two other variables (García & Vallejo 2011).* (Lawson & Samson 2001) explicitly practiced the dynamic capabilities to the innovation studies. Notably, they established a model that pointed to global dynamic capabilities, categorizing and operationalizing them in seven main elements (e.g. vision and strategy, harnessing the competence-base, organizational culture, and climate, management of technology, knowledge management, information sharing, and collaboration.) An explanation in detail of each dynamic capability is provided in Table 12. Further, DCs

theory was linked with sustainability by (Wu et al. 2012) in where they developed a conceptual framework examining the necessary capabilities that firms need to gain competitive advantage and sustainability. There are also studies that demonstrate the influence of Dynamic Capabilities in creating Disruptive Innovation specifically in Innovation Capacity (IC) (ability to continuously transform knowledge and ideas into new products, processes, and systems for the benefit of the firm and its stakeholders (Lawson & Samson 2001.) To demonstrate this, the author used the Innovation Lifecycle on Dynamic Capabilities (Čiutienė & Thattakath 2014). Alike, there are studies that examine absorptive capacity (AC) creation (ability to conceptualize new ways of doing things, to understand the changing environment and to be open to new ideas to acquire new knowledge and think in new ways (Cohen & Levinthal 1990; Zahra & George 2002), which fosters subsequent innovation and argues that organizational compatibility facilitates AC. More precisely, AC **mediates** the relationship between organizational compatibility and innovation in a relational context (Sáenz et al. 2011). For better understanding, a **mediation model** *is one that seeks to identify and explain the mechanism or process that underlies an observed relationship between an independent variable and a dependent variable via the inclusion of a third hypothetical variable, known as a* ***mediator variable****. Mediation analysis facilitates a better understanding of the relationship between the independent and dependent variables when the variables appear not to have a definite connection (García & Vallejo 2011).* Therefore, in Figure 3 the Conceptual Framework for studying the enablers of big data and predictive analytics which impacts SSCA performances shows a moderator model that will be explained in the following section.

Likewise, we can find in the literature linkages of DCs with sustainable supply chain and DCs process-oriented with big data analytics as well (Wu et al. 2012; Beske 2012; Wamba et al. 2017). But despite all these studies, many large firms still fail to develop and implement Big Data and Predictive Analytics within Sustainable Supply Chain due to the lack of the right capabilities to support innovation (Assink 2006; Čiutienė & Thattakath 2014).

3.2.2 Absorptive Capacity View (ACV)

This study follows the absorptive capacity view (ACV) as a Dynamic Capability (DC) that in organizations can play a significant role in both assimilation and extraction of value from BDPA. Absorptive Capacity (AC) is ‘‘the ability of a firm to recognize the value of new and external information, assimilate it, and apply it to commercial ends which is critical to its innovative capabilities (Cohen & Levinthal 1990).” (Malhotra, A., Gosain, S., & Sawy 2005) perceive it as ‘‘the set of organizational routines and processes by which organizations acquire, assimilate, transform, and exploit knowledge to produce dynamic organizational capabilities.” Furthermore, in the context of technology assimilation, AC is treated as an asset in the form of prior knowledge possessed by organizations that foster innovation (Roberts et al. 2012). BDPA as a knowledge infrastructure could enhance knowledge transfer from supply chain partners and increase the recipient firm’s AC. Further, in relevance to extracting value from

technology like BDPA, AC can be conceptualized as a DC which could complement BDPA capability in generating business value. Additionally, AC is used by many researchers to explain organizational learning from a strategic management perspective. AC is a multi-level and multi-dimensional construction. It relates to the individual level to the inter-organizational level and can have many interrelated capabilities (Roberts et al. 2012; Wang et al. 2014). In the supply chain context, the critical information needed to improve supply chain performance is mostly available in external sources (Dobrzykowski et al. 2015), not readily accessible for decision-making. Nevertheless, BDPA can provide critical information in real-time and enhance the organizational capability to acquire, assimilate, transform, and exploit the information and knowledge for commercial ends. Moreover, firms with low absorptive capacity (AC) would find it difficult to adopt innovative BDPA technologies like for example Elasticsearch, Kibana, MapReduce, and Beats (Ebner et al. 2014; Elastic.com 2017). Likewise, it can be argued that even if BDPA resources are well established at the organization level, it becomes obsolete when an organization does not exhibit absorptive capacity. Indeed, AC is considered as one of the prerequisites of BDPA initiatives or successful implementation (Kabir & Carayannis 2013; Wang et al. 2015; Wamba et al. 2017; Arunachalam et al. 2017).

However, many large firms still failing in developing implementation plans of this technology due to the lack of the right capabilities to support innovation (Čiutienė & Thattakath 2014; Assink 2006). Few studies investigate the effect of the combination of absorptive capabilities on supply chain performances. Comparatively, (Wu et al. 2006) argue that the use of capabilities may help organizations to achieve or sustain competitive advantage. Academic researchers related assimilation as a capability that can impact supply chain performances positively (Benjamin T. Hazen et al. 2016; Gunasekaran et al. 2017), but the influence of several organizational factors/enablers remains ambiguous (Oliveira et al. 2012; Schoenherr & Speier-Pero 2015; Gunasekaran et al. 2017; Arunachalam et al. 2017; Wamba et al. 2017).

In this thesis, the **moderator variables** (factor/enablers of BDPA and absorptive capacity (AC) are used in a **multiple moderator model** to understand the impact between BDPA implementation and SSCM performances.

Table 12: Dynamic Capabilities Dimensions

Dimensions	Components	Role	Descriptions	Authors
Exploration	1. Prior knowledge 2. Knowledge scanning 3. Knowledge source	1. Know-how (firm intellectual property) 2. Benchmarking 3. New connections	Recognizing and understanding potentially valuable new knowledge	(Zahra & George 2002; Todorova & Durisin 2007;

			outside the firm.	Lichtenthaler 2009; Sáenz et al. 2014)
Assimilation	1. Understanding	1. Interpretation 2. Comprehension 3. Learning	Transformative learning through the combination of existing knowledge.	(Cohen & Levinthal 1990; Zahra & George 2002; Tu et al. 2006; Sáenz et al. 2014; Lichtenthaler 2009)
Exploitation	1. Use 2. Implementation	1. Core competencies 2. Harvesting resources	Using assimilate knowledge to create new knowledge outside firms.	(Grimpe & Sofka 2009; Fabrizio 2009; Sáenz et al. 2014; Tu et al. 2006; Todorova & Durisin 2007)

3.2.3 Institutional Theory

According to (Benjamin T. Hazen et al. 2016), Institutional Theory seeks to explain how an organization's external environment impacts the organization's structures and processes. He mentioned that institutions could be defined by a set of rules within an environment that form a pattern of acceptable behavior among those who operate within that environment. He thinks that organizations that become part of the institution conform to the behaviors of the institution and are difficult to change. The adoption of organizational practices typically occurs via coercive (exerted by those in power), normative (exerted by social influences), or mimetic (exerted to imitate success) influences on the organization (DiMaggio & Powell 1983). The institutional theory may be particularly useful within a supply chain context. As an institution, the supply chain induces partners to take on behaviors that individually the organization may not have chosen as a rational choice (Daudi et al. 2016). Applications across all three aspects of the 3BL are applied. Coercive pressures have been found crucial in the adoption of environmentally sustainable practices (Zhu et al. 2007; Sarkis et al. 2011). Similarly, normative inducement examples can be found in the formation of social organizations such as industry groups and professional societies (Zsidisin et al. 2005; Zsidisin et al. 2008). Finally, the mimetic force examples can be seen in the adoption of supply chain practices that an organization perceives to be successful, profitable, or cost-effective (Ketchen & Hult 2007). In the social context (Dubey et al. 2017) introduce

organizational culture (OC). However, the Dynamic Capability View (DCV) has failed to examine this context within the selection of the resources are embedded. Thus, (Dubey et al. 2017; Benjamin T. Hazen et al. 2016) argued that the institutional pressures may offer a better explanation to explain the motivation of the organizations which seek beyond economic rationality. Therefore, this research seeks to address the missing link of the adoption of BDPA on SSCA using an integration of institutional theory and DCs.

3.3 Problem Definition and Research Gap

BDPA has the capability of transforming the decision-making process by allowing enhanced visibility of firm operations and improved performance measurement mechanism. Additionally, practitioners and scholars are wondering how BDPA impact the 3BL in sustainable SCA. However, it is limited the understanding of the important role of BDPA and SSCA that enables the format needed for taking strategic decisions related to sustainability. Table 12 below, shows a summary of several research themes and gaps in SSCA enablers and Big Data Analytics.

Table 13: Summary of several research themes and gaps on SSCA enablers and Big Data Analytics. Source: Author

Journal Tittle	Done	Missing	Future Research
Analysis of enabler for implementation of sustainable supply chain management a textile case. (Diabat et al. 2014; Oelze 2017)	Identify influential enablers for SSCM by using Interpretive Structural Modelling (ISM)	The study was conducted in the textile sector and only **13 enablers** were considered in this research in **India.**	Conduct the study **in other countries**, and identify **more enablers**.
Sustainable Supply Chain Analytics: Grand Challenges and Future opportunities. (Firouzeh et al. 2017)	Identification of several drivers and barriers against successful implementation of SSC.	**Influence degree** of each **factor** for facilitating/delaying sustainability **adoption is unknown.**	Estimate the **impact factor of enablers/disruptions** using **predictive analytics.**
Big data analytics in logistics and supply chain management: Certain investigations for research and applications (Wang et al. 2016)	**Introduction of the concept of sustainable SCA** that refers to the use of methodologies and techniques to collect, analyze, disseminate, and use sustainability-related information for both strategy and operations.	Limited understanding on the **important role** of **BDPA** and **SSCA** as the **'glue'** that enables the format needed for **taking strategic decisions related to sustainability**	Understand SCA and BDBA as **strategic assets** that should be **integrated** across business activities to **enable** integrated enterprise **business analytics capabilities.**

Table 13 Continue: Summary of several research themes and gaps on SSCA enablers and Big Data Analytics. Source: Original Research by the Author

Journal Tittle	Done	Missing	Future Research
Big Data and Predictive for supply chain sustainability: A theory-driven research agenda (Benjamin T Hazen et al. 2016).	Review of **8 theories** that can be used **to clarify** the nature of **BDPA impact on SSC**	Examine how BDPA **can increase measures** of the **other aspects** of **sustainability on the supply chain**	**Exploring** how BDPA **can affect** financial, social, and environmental performance measures.
Can big data and predictive analytics improve social and environmental sustainability? (*Dubey, Gunasekaran, Childe, et al. 2017).*	**Investigation of the effects of BDPA on (SP) and (EP)** using Organizational Culture Capability, **(DCV), and extension of (RBV).**	• The study gathered data at one point in time. • The current study focuses on managers' perceptions rather than actual performance. • The **DCV has failed** to **examine the social context** within which selection of the re-sources are imbedded.	• A longitudinal study would enrich our under-standing. • Use **more objective data** sets to predict the impacts of BDPA on SP/EP. • Examine the adoption of **BDPA using integration of institutional theory and DCV**

The literature on SSCA and interaction approach has addressed several research themes and gaps as you will see in Table 13 above on the enablers of Big Data on Sustainable Supply Chain Analytics and its successful implementation within companies. Further investigation and empirical work are needed to fill the gaps related to how effective are the big data and predictive analytics tools on SSCA for decision making and how do internal practices compete with external pressures in the adoption of BDPA for SSCA policies and practices. The research gaps can be summarized as follows :

- Degree of influence of each factor for facilitating/delaying sustainability adoption is unknown.
- Limited understanding of the important role of BDPA and SSCA as the 'glue' that enables the format needed for taking strategic decisions related to sustainability**.**
- Further exploration of the role of BDPA as a resource that enables supply chain sustainability.

Therefore, based on the literature and identified gaps, the overall aim of this thesis is:

"A qualitative analysis to investigate the enablers of big data analytics that impacts sustainable supply chain."

This overall aim is used to devise the main research questions that will be described in the next section.

3.4 Research Questions

By addressing the overall aim of the thesis and research gaps identified above, the following research questions are posed in Table 14:

Table 14: Key Tenets of Theories and Research Questions (Dubey, Gunasekaran, Childe, et al. 2017; Benjamin T. Hazen et al. 2016; Wang et al. 2016; Firouzeh et al. 2017)

Theory	Key Tenets of Theory	Research Questions
Institutional Theory	*Provides a lens to observe the **impact** of an organization's **external environment** on the organization's structure and operations.*	**How do internal practices compete with external pressures in the adoption of BDPA for SSCA policies and practices?**
Absorptive Capacity as a Dynamic Capability	Creates new firm resources by **searching, acquiring, assimilating, transforming and exploiting external knowledge with internal resources** and act as a process framework for innovation . In the context of **technology assimilation**, **AC** is treated as an **asset** in the form of prior **knowledge** possessed by organizations which **foster innovation.**	**How the use of certain tools and techniques of BDPA impacts the effectiveness of decision-making on sustainable supply chain analytics?** **What are the influence degrees of certain enablers for an effective implementation of SSCA practices on companies?**

1. **How the use of certain tools and techniques of BDPA impacts the effectiveness of decision-making on sustainable supply chain analytics performances?**

   A significant portion of the existing literature has introduced the concept of sustainable supply chain analytics (SSCA) that refers to the use of methodologies and techniques to collect, analyze, disseminate, and use sustainability-related information for both strategy and operation. However, the authors call for more research on tools and techniques that enable sustainability decision-making through SSCA.

2. **What are the influence degrees of certain enablers that impact the effective implementation of BDPA on SSCA practices within companies?**

   Researchers have already identified several drivers and barriers against the successful implementation of SSCA. However, the influence degree of each

enabler for facilitating/delaying sustainability adoption is unknown. Authors are advised as future research to estimate the impact factor of enablers/disruptions using big data and predictive analytics.

3. **How do internal practices compete with external pressure in the adoption of BDPA for SSCA policies and practices?**

   In the literature, coercive pressures have been found crucial in the adoption of environmentally sustainable practices. Similarly, many examples can be found in the formation of social organizations such as industry groups and professional societies. Finally, the mimetic force examples can be seen in the adoption of supply chain practices that an organization perceives to be successful, profitable, or cost-effective. However, future investigation work about this impact is needed, valuable, and highly informative for a holistic understanding of the overall nature of the contemporary firm and its place in both, its competitive market and larger world.

3.5 Synthesis of the Literature Review and Conceptual Framework

The literature review has been instrumental in the development of the conceptual framework. This way, the scope of this study covers the following key elements: a. Big Data and Predictive Analytics b. Sustainable Supply Chain Performances c. Internal/External Enablers/Factors of Sustainable SCA implementation and d. Absorptive Capacity. It addresses the knowledge gap in the academic literature regarding "***A qualitative analysis to investigate the enablers of big data analytics that impacts sustainable supply chain."***

The conceptual framework of this thesis is shown in Figure 3 and it is composed of four elements based on the central concepts and themes that are discussed in the previous chapters which are:

- ***Internal/External Enablers:*** These are the factors that **motivate and mediate the adoption** of big data analytics and a sustainable supply chain. The identified enablers have been **divided into two groups**, according to the observations of (Walker et al. 2008; Lin et al. 2010)
  - ***Internal***
    - **Organizational Factors:** Skillful policy entrepreneurs, Values of owners, Involvement of employees, Reduction of costs, Pressure on Investors, Quality Improvement.
  - ***External***
    - **Regulations:** legislative and regulatory compliance. Example: ISO 14000 certification.
    - **Customers:** pressure by customers to SSCM, marketing pressures, collaboration with customers.

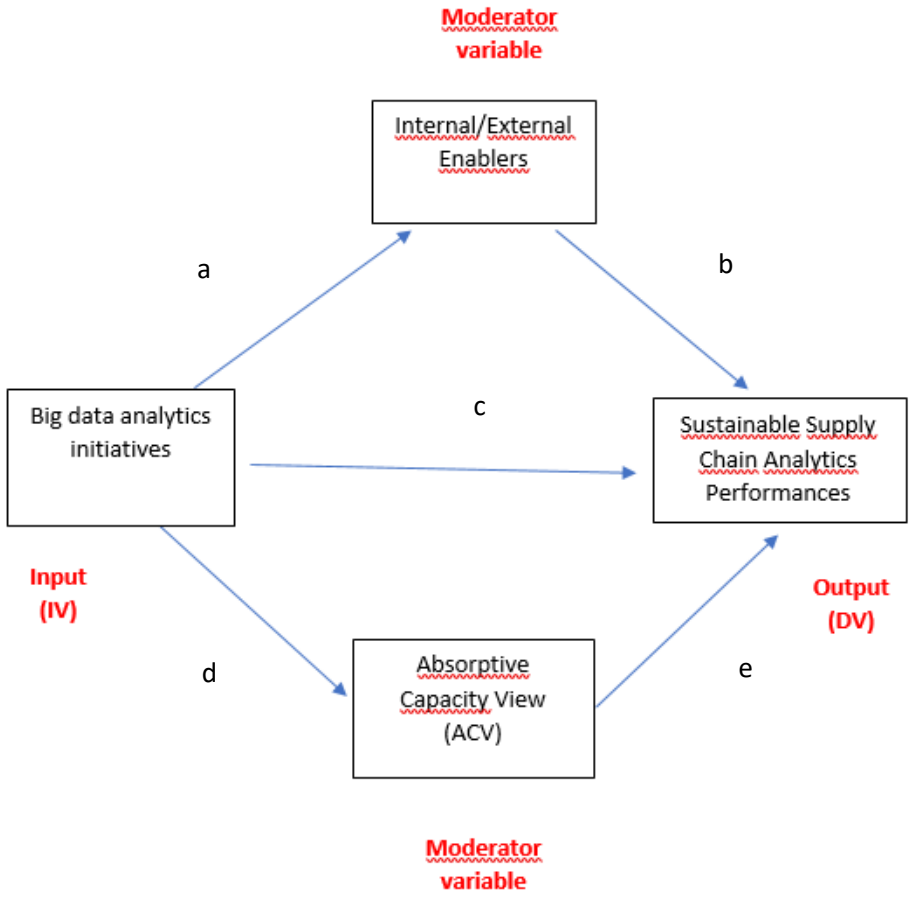
- **Competition:** gaining competitive advantage, improving firm performance, etc.
- **The societal driver:** public pressure, consumer criticism, etc.

❖ **SSCA performances:** The second element considers the relevance of SSCA performances. SSCA is one that includes measures of **profit** and **loss** as well as **socia**l and **environmental** dimensions (Carter & Rogers 2008; Linton et al. 2007). However, SSCA has been primarily just focused until now on **economic** and **environmental** aspects and there is an **under-explored** around the social and human aspect of sustainability in business practices that have not been investigated in-depth and it will be included in this study.

❖ **Big Data and Predictive Analytics:** The third element considers the relevance of new technologies. BDPA were chosen in the study because they are impacting many areas, for example, in retailing firms: to improve e-commerce needs, customer segmentation, fraud reduction, make just-in-time recommendations (Tweney 2013). In the healthcare sector, it is expected to reduce operational costs and improve the quality of life (Liu 2015). Understanding the uses and implications of big data and predictive analytics, it will be urgent that SSCA makes traditional models of production, distribution, and demand obsolete in some process areas.

❖ **Absorptive Capacity**: The fourth element considers the relevance of dynamic capabilities specifically **absorptive capacity** as a **mediator factor** and pre-requisite for innovation implementation. (Kabir and Carayannis 2013; Wang et al. 2015; Wamba et al. 2017; Arunachalam et al. 2017). Studies linking DCs with SSCM practices, and DCs influences in creating innovation (Beske 2012; Čiutienė & Thattakath 2014). However, many large firms still fail to implement BDPA due to the lack of the right capabilities to support innovation (Assink 2006; Čiutienė & Thattakath 2014).

Figure 3: Conceptual framework to study the enablers of big data and predictive analytics that impacts on SSCA performances. Source: Author



The purpose of the conceptual framework is to conduct the research process and assist in preparing the protocol for my questionnaire and data gathering from the companies and SC professionals.

3.5 Research Approach

This thesis adopted the stance of a mixed-method approach because it provides the strongest evidence and explores a contemporary phenomenon within its real-life context especially when the boundaries between phenomenon and context are not clear. Furthermore, it would be critical for the theory that it will be used in this study whose propositions are believed to be true. The mixed-method approach can be used to determine whether the propositions are correct or whether some alternative set of explanations might be more relevant (Yin 2014), thusly being appropriate when a few previous studies have been conducted on information-based linkages (Benbasat 1987). This method enables researchers to answer **"how"** and **"why"** questions while considering how a phenomenon is influenced by the context within which it is situated (George & Bennett 2005; Seuring 2008; Levy 2008; Yin 2014). Likewise, the adoption of a single-case study is consistent with (Stuart et al. 2002; Voss et al. 2002), which suggested that it is appropriate in this research methodology to map the field of supply chain management because it may facilitate current research in particular for four major purposes: exploration, theory building, theory testing, and theory extension/refinement. Furthermore, the adoption of one case study has been considered with previous studies in the area of innovation, for example, (Chen & Jaw 2009; Lawson & Samson 2001). The case selection strategy has been driven by the desire to analyze a representative case for industry peculiarities (Seuring 2008; Yin 2014), by using an information-oriented approach (Flyvbjerg 2006), and the five-stage case research process (Stuart et al. 2002). It has been choosing a deeply innovation-sensitive industry that fulfills the requirements for such a dynamic business environment and, it is an exciting case from different vantage points (Jack van der Vorst 2002; Beske et al. 2014). First, it is under constant from the public (Manning et al. 2006). Secondly, it relates to environmental issues like loss of fragile habitats (e.g. wetlands, mangroves) and occupational and public health concerns. Thirdly, markets that target customers with a high awareness of all three dimensions of sustainability are exposed to dynamic changes in customer perceptions and expectations (Beske et al. 2014).

The research subject of "Investigating the enablers of Big Data on Sustainable Supply Chain Analytics" is complex and dynamic as it is concerned with the interaction and change of internal and external processes that take place within an inter-organizational context. A quantitative and qualitative approach based on questionnaires and case studies are more appropriate to this thesis due to the nature of research gaps and questions. The case study approach has enabled collecting data from the employees of "THE COMPANY A" on how sustainable supply chain analytics are implemented using big data strategies. On the other hand, the questionnaires target the supply chain professionals who were able to identify the current problems of the supply chain field in their firms.

The research presented in this manuscript was conducted in two phases. The first phase was the development to understand the enablers. A questionnaire was carried out, it was developed on Google forms based on the literature review and inspired by (Creswell 2003; Fallis 2005; Watson et al. 2004; Wacker 1998) (bit.ly/enablers_ssc_questionnaire). Even though on-site visits were not possible, the questionnaire was sent directly via email and messages (e.g.

WhatsApp and Facebook Messenger), contacting around 50 people, and posted – both as free and sponsored content - through social networks such as LinkedIn and Facebook. The audience of the social network groups was reported to be around 10k people; however, the number of people was not measured effectively because many external variables were out of control. The aim of this study is to get at least 35 valid answers to conduct the statistical analysis. Target participants are senior executives from different countries, able to identify the problem of the supply chain to which their firms belong, and who are responsible for SCM and thus they were qualified to provide a valid response to this research. All of them were asked to complete and return the questionnaire form with scales measuring the enablers of implementation of sustainable supply chain analytics. Then, the answers to this questionnaire will be analyzed with Exploratory Factor Analysis.

The second phase consisted of conducting a case study with a large Panamanian company and their employees that is denominated: "THE COMPANY A", due to a **nondisclosure agreement** between the author and the company. The analysis process was based on the analysis of a huge quantity of data (e.g., massive items) that the company provided me; the chapter 4 will focus on data analysis usefulness with a big data analytics approach to enhance SC operations using real operational datasets from "THE COMPANY A" and best practices recommendations for their continuous improvement. The dataset was referred to five-year operations of the purchasing department and extracted from their Enterprise Asset Management (EAM) software Maximo. The company is new to BDPA applications. Thus, Advanced Analytics can prove productively in decision-making for them.

3.6 Research Credibility

Quality research needs to be rigorous which can be achieved through validity and reliability criteria. These criteria of judging the research quality is applicable whether the research type is quantitative or qualitative. Although the criteria for judging the rigor of case studies provided by (Yin 2014) holds the positivist views, they are adopted in this thesis to ensure the integrity of the research process and its rigor. The four criteria for judging the credibility of research on this thesis are ***construct validity, internal validity, external validity, and reliability.***

3.6.1 Construct Validity

Construct validity is concerned with the extent to which the research investigates what it is determined to investigate and look for multiple sources of evidence (Stuart et al. 2002). The bias and subjectivity of the researcher are always under criticism in qualitative research. To enhance the construct validity of this thesis, multiple sources of evidence and information were used such as questionnaires, secondary sources of information such as "THE COMPANY A" website, processes flowcharts, reports and presentation materials provided by the employees of the company. Also, by meeting more than one person in the company to get their views and answers to the questions that enhanced the accuracy of data and checking the information provided by the participants. The weekly presentations and meetings were helpful in writing the case study accurately and doing the analysis within and across the case. After writing the case, a report was sent to the company that contained the case study description,

main findings, and some recommendations. “THE COMPANY A” was asked to check the report for accuracy and correctness of the data and whether there were points to be explained or added. “THE COMPANY A” provided valuable comments on the sent reports and in some situations; telephone calls were made to discuss some of the findings in the reports or make clarification when it was needed. This step was valuable and important to make sure about the correctness of captured data and enhancing the construct validity of this thesis.

3.6.2 Internal Validity

Internal validity is related to the coherency of the data and empirical work findings. There is a need to present a valid argument and reasoning to defend the research findings. Internal validity can be achieved by building a framework that shows the links between elements of the study and matching them with the empirical findings (Gibbert et al. 2008). In this thesis, internal validity was achieved by using the framework to link the findings from the case studies to the research questions. The questionnaire protocol was used to enhance internal validity as it is documented in the research process. Before engaging in a single case study, a set of pilot studies were conducted, and they assisted in testing and refining the research questions and the questions in the case study. Another way of achieving data validity was by seeking in the meetings the employees of the organization to check the data in order to prevent misunderstanding and enhance the validity of the findings.

3.6.3 External Validity

External validity or generalizability is about the applicability of the research work findings to a broader context or extending the results to other situations. A single case study was used in this thesis to create a high-quality theory because this type of case produces extra and better theory and a deeper understanding of the current subject: ***“A qualitative analysis to investigate the enablers of big data analytics that impacts sustainable supply chain.”*** As argued by (Gustafsson 2017) the single case studies richly can describe the existence of phenomenon and it is better to make a single case study than a multiple case study when the writer wants to study, for example, a person or a group of people. When a single case study is used the writer also can question old theoretical relationships and explore new ones. This is because a more careful study is made. Also, the thesis adopted a questionnaire as a research strategy in order to capture the different perceptions of the people and the company on big data applications on sustainable supply chain analytics. The questionnaire used five-point Likert scales to measure the constructs. Scales to measure each of the constructs were developed based on prior studies as much as possible. Some measures were modified to adapt to this research.

3.6.4 Reliability

Reliability is concerned with the repeatability of the same results if the research is carried out by another researcher following the same procedure. As indicated by (Meredith 2002), reliability is attained by *“applying the resulting case study theory to a somewhat different set of conditions, which very well might result in a different prediction. Thus, even though the*

prediction is different, the same theory is being tested". The research protocol given to "The Company A" specifies how the research has been conducted and can provide a useful source for the readers and researchers to have details on the research process. Data was collected from the questionnaire and the data of five years given to "The Company A". The answers to the questionnaire were analyzed in R with Exploratory factor Analysis to enhance the reliability of the research findings (Ramsay 1998). Table 15 provides a summary of how credit has been achieved in this thesis.

Table 15: Credibility achievement in this thesis. Adopted from (Wieck, E., Blome, C., Paulraj, A., and Henke 2012)

Credibility Criterion	Research Phase			
	Design	**Case Selection**	**Data Collection**	**Data Analysis**
Construct Validity ***(the extent to which the research investigates what it is determined to investigate)***	Research questions, frame of reference and questionnaires were developed based on literature review on SSCA, BDPA and integration approach.	N/A	-A questionnaire was developed on Google forms based on the literature review. -Multiple meetings through Skype with key personal of "The Company A."	-Multiple documents, sources, and data of five years given by company A. -A factor analysis was carried out to analyze the questionnaire sent to SC professional. - Reports on case study were sent to "The Company A" for validation.
Internal Validity ***(Coherency of the data and empirical findings*****)**	Build a framework to show the links between the findings from the questionnaires, case study to the research questions.	-Selection criteria for the case study as it is explained in the Research Protocol	- Multiple meetings through Skype with key personal of "The Company A." -Research and meeting protocol that document the case study process with "The company A"	- Case comparison and pattern matching within and among the questionnaires.

			-Reports on case study were sent to "The Company A" for validation.	
External Validity ***(Applicability of the research work findings to a broader context or extending the results to other simulations)***	-Target participants of the questionnaire were senior executives able to identify the problem of the supply chain to which their firms belong. -A case study with "Company A" operating in the maritime industry. -Research protocol and criteria for the case study selection.	-Meetings through Skype with the employees of "The Company A" for the case selection.	-A questionnaire was developed on Google forms based on the literature review and research questions. -Multiple meetings through Skype with key personal of "The Company A."	-Explain the context of the findings and generated knowledge in each case study. -Within and Across case study and questionnaire analysis. - The questionnaire used five-point Likert scales.
Reliability ***(Repeatability of the research procedure and methodology)***	-Research and meeting protocol that documents the case study process with "company A."	-Selection criteria for the case study as explained in the Research Protocol	-Multiple meetings through Skype with key personal of "The Company A, and multiple documents, sources, and data of five years given by the company.	-Statistical Analysis using Exploratory Factor Analysis. - The statistical software R was used to carry out the Exploratory Factor.

Chapter Four: Data Collection, Data Analysis, and Results

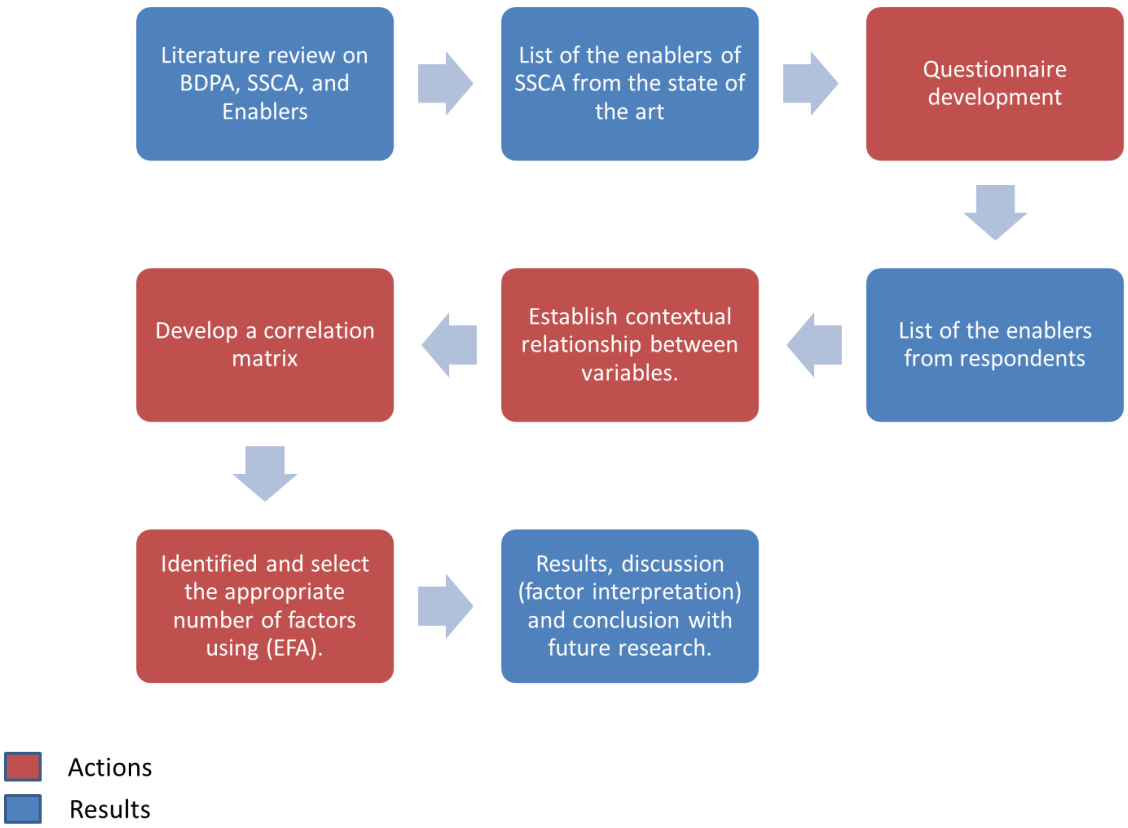
4.1 Data Collection Process

4.1.1 Introduction

While the investigation reached a large audience, many people did not accept the invitation to participate; some respondents answered, however, the initial contact justifying the refusal with the fact that they think they do not have the required knowledge to answer or the proficiency in big data and analytics fields. Few answers have also been discarded because people abandoned the questionnaire before completing it; software limitations prevent from using the partial answers. Thus now, this exploration got only 35 valid answers on the questionnaire.

The companies that participated in the questionnaire were chosen using two criteria. First, the firms chosen for the investigation exceeded the criterion of annual sales of U.S. $100 million. They have at least 100 employees and have operated for over five years. Second, for each company, we wanted a preliminary contact in the areas of supply chains, be a professional in this field. These contacts were reached either through the company's website or through e-mail correspondence. Target participants were senior executives able to identify the problem of the supply chain to which their firms belong, and who are responsible for SCM and thus were qualified to provide a valid response to this research. All of them were asked to complete and return the questionnaire form with scales measuring the enablers of implementation of sustainable supply chain analytics and BDPA.

Figure 4: Process flowchart as follows in this section. Source: Author



4.1.2 Facts about the questionnaire on enablers for sustainable supply chain analytics (SSCA) implementation

The questionnaire was made of 29 questions, grouped in 3 main parts. The first part is the demographic part, asking for the age, gender, experience in the field and more details regarding the working position. The second part is the core of the study. It contains the questions aimed to investigate the external and internal enablers of SSCA and big data. These have been chosen based on the state of the art explained in Chapter 2, Part 2.8: "Factors and enablers for implementing sustainable supply chain analytics." The third part focuses on the use of data analytics within a company.

These questions produce 58 variables (numerical + categorical), but only 43 variables were suitable for statistical analysis: few of them were removed as many respondents skipped the answer. The non-numerical demographical variables were used only for qualitative purposes and not in the quantitative one. For example, "**Staff doing the input need to know more about the end results"** was one of the variables.

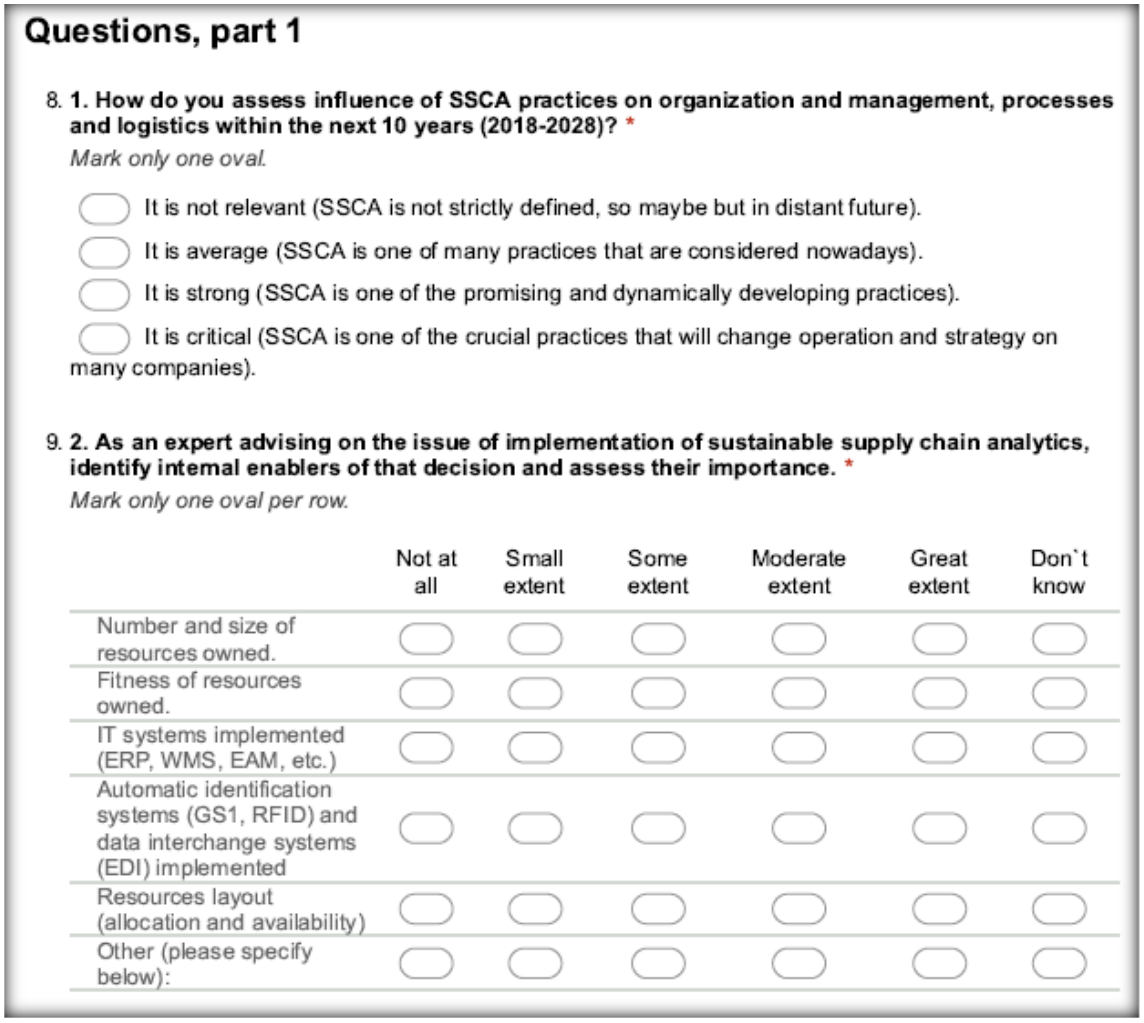
At the end of the questionnaire, I left some blank fields for the users to give me suggestions and comments, in order to receive feedback about more enablers that I didn't take in account for future studies, and at the same time receive feedback regarding how I can improve the questionnaire.

As mentioned before, this dataset contains 35 valid responses for 43 different variables that logistics and supply chain professionals and researchers considered while using or not analytics tools such as BDPA, but we had to consider just 43 variables. The survey questionnaire was framed using the 5-point Likert (Abdul 2010; Leung 2011) scale following below:

i. Not at all
ii. A small extent
iii. Some extent
iv. A moderate extent
v. A great extent
vi. Don’t know

You can access the complete questionnaire in Annex a. In Figure 5, you will see just a screenshot extract questionnaire that was created in Google Forms by the author.

Figure 5: Screenshot Extract: "Questionnaire on enablers for sustainable supply chain analytics (SSCA) implementation". Source: Author



Questions, part 1

8. **1. How do you assess influence of SSCA practices on organization and management, processes and logistics within the next 10 years (2018-2028)?** *

Mark only one oval.

- ◯ It is not relevant (SSCA is not strictly defined, so maybe but in distant future).
- ◯ It is average (SSCA is one of many practices that are considered nowadays).
- ◯ It is strong (SSCA is one of the promising and dynamically developing practices).
- ◯ It is critical (SSCA is one of the crucial practices that will change operation and strategy on many companies).

9. **2. As an expert advising on the issue of implementation of sustainable supply chain analytics, identify internal enablers of that decision and assess their importance.** *

Mark only one oval per row.

	Not at all	Small extent	Some extent	Moderate extent	Great extent	Don`t know
Number and size of resources owned.	◯	◯	◯	◯	◯	◯
Fitness of resources owned.	◯	◯	◯	◯	◯	◯
IT systems implemented (ERP, WMS, EAM, etc.)	◯	◯	◯	◯	◯	◯
Automatic identification systems (GS1, RFID) and data interchange systems (EDI) implemented	◯	◯	◯	◯	◯	◯
Resources layout (allocation and availability)	◯	◯	◯	◯	◯	◯
Other (please specify below):	◯	◯	◯	◯	◯	◯

4.1.3 Insights of the "Questionnaire on enablers for sustainable supply chain analytics (SSCA) implementation"

The questionnaire has been running for 4 months (Mach 2018-July 2018), from which data underlined the following insights illustrated in Figures 6 to 9 and showed in Annex a. From the large group targeted at the beginning, only 104 people viewed the questionnaire (measured through link clicks). Interestingly, while the social network audience was far bigger, it accounted for only 42% (almost half of which from the sponsored post) while direct contact brought the remaining 58%. Regarding the demographics, 23.5% of participants came from Europe, 73.5% from Latin America, around 3% from the US and the Caribbean. While these numbers are encouraging, unfortunately only 35 people completed the questionnaire. This finding is a possible indication that either the people clicked only to understand more about the questionnaire and left because they were not interested in participating, or they did not complete the

questionnaire because it was too long or complex for them. This last hypothesis comes from some direct feedback from a few known participants. It cannot confirm this on a large scale because incomplete questionnaires are not recorded by the system; this limitation will be considered in the following works. Interestingly, while participants from LATAM and Europe represented the same percentages, people from LATAM completed the questionnaire twice as much as European people did. In other countries were both from the Caribbean and Europe. It allows the users to express their opinions on a few aspects putting free text fields to fill. The elements that were highlighted by participants were especially the **legal framework** (e.g. speed in applied regulations), **lack of training skills**, and **labor cost** as enablers for sustainable supply chain analytics. They also indicated that **grow scalability and compromise/integration** with all management levels are important intangible assets to consider in the equation.

Figure 6: Area/Department in the Company (35 responses). Source: Author

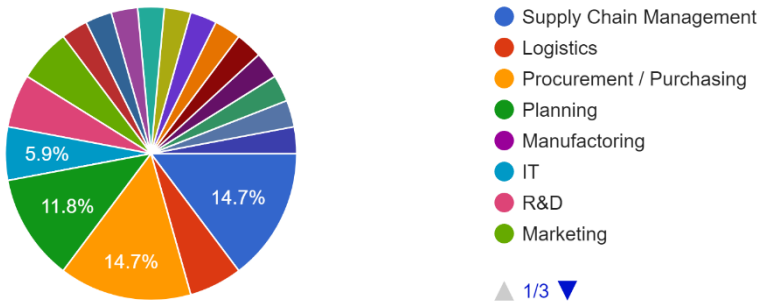


Figure 7: Role within the Area/Department (35 responses). Source: Author

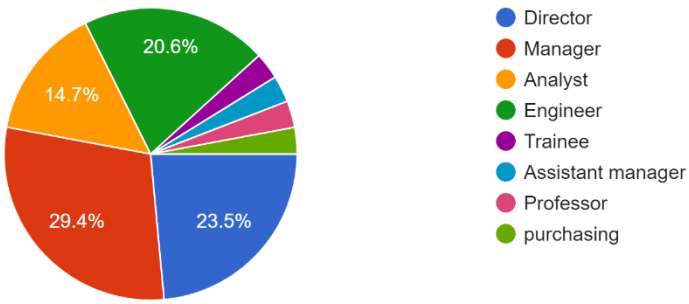


Figure 8: Gender (35 responses). Source: Author

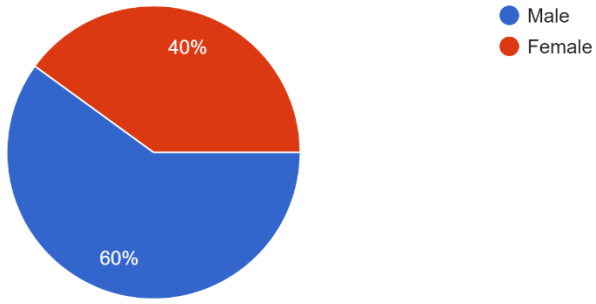
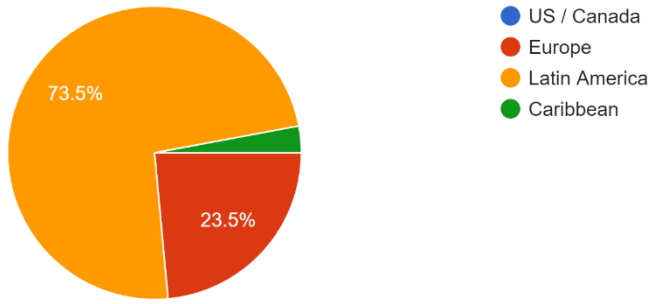


Figure 9: Geographical area of the company (35 responses). Source: Author



After receiving the answers from the respondents, the next step is to determine the variables that will be used in this study. The variables are shown in Figure 10:

Figure 10: Excel extract screenshot. List of variables from the respondents' answers. Source: Author

Age
Years.of.Experience
Influence.of.SSCA.within.10.years
Importance.of.Number.and.size.of.resources.owned
Importance.of.Fitness.of.resources.owned
Importance.of.IT.systems.implemented
Importance.of.Automatic.identification.systems.and.data.interchange.systems
Importance.of.resources.layout..allocation.and.availability.
Intangible.Assets..Competitive.position.
Intangible.Assets..Range.of.the.offer.
Intangible.Assets..Territorial.scope.of.business.activity.
Intangible.Assets..Flexibility.of.operation.and.innovation.transfer.
Intangible.Assets..Organizational.maturity.
Intangible.Assets..Organization.culture.
Intangible.Assets..Efficiency.at.operational.level.
Intangible.Assets..Other..please.specify.below...
Importance.of.commitment.from.management.to.achieve.sustainability
Importance.of.for.top.management.to.avoid.greenwash
Importance.of.governmental.regulations
Importance.of.the.cost.of.implementing.green.logistics
Importance.of.international.agreements
Importance.of.information.and.business.analytics.create.a.competitive.advantage
Impact.of.domestic.and.environmental.policies
Importance.of.customers.awareness
impact..of.big.data.tools.for.sustainability.
How.has.your.access.to.useful.data.changed.during.the.past.year.....
How.often.do.you.feel.you.have.the.right.data.needed.to.make.key.business.decisions.....
Data.is.timely
Data.is.Relevant
Data.is.Reliable
Data.is.Accessible
Data.is.Consistent
Data.is.Complete
just.began.to.apply.analytics
aren.t.sure
haven.t.acted
do.not.use.analytics.to.drive.strategic.decisions.
We.are.using.analytics..but.so.are.our.competitors.
Analytics.is.not.a.priority.for.senior.management.
Staff.doing.the.input.need.to.know.more.about.the.end.results
Analytics.help.improving.innovation
Your.organization.uses.customer.feedback.to.inform.decision.making
Use.of.detailed.data.to.tailor.specific.offerings.to.customers
Customers.are.engaged.with.your.organization
Customer.intelligence.has.improved.since.last.year
Effectiveness.of.lean.processes.and.cutting.of.wastes
Green.Purchasing.helps.sustainability
Would.you.....use.BDPA.to.turn.your.purchasing.more.green.or.sustainable..
Would.you.....implement.BDPA.if.it.could.improve.your.purchasing..
Would.you.....implement.BDPA.if.it.could.make.your.company.more.green..

4.2 Data Analysis Process

The objective of this study is to understand **the hidden latent factors** driving the adoption of big data analytics in the supply chain. This study is unable to measure these factors directly because it is exploring what they are. For this reason, it had been used statistical techniques that can help to understand the broad concepts that define the dimensions. These hidden factors are expressed through the questionnaire answers, and the questions are the independent variables to measure.

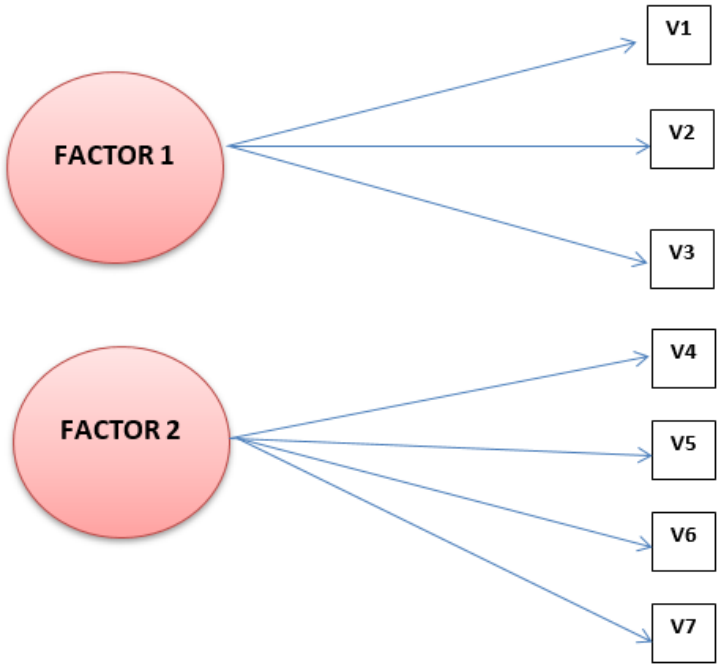
Considering the possible available statistical analysis such as simpler statistics or machine learning, I decided to use a powerful and commonly one like **Exploratory Factor Analysis (EFA**). Maybe the readers will ask themselves, why didn't I use a simpler statistic? You can, but the objective was to have the relationship between factors and variables as a whole picture; or maybe they will ask, why didn't you use machine learning? It was too powerful, not needed to understand the factors, and I do not get enough samples within the questionnaires. Thus, EFA is a more complete analysis technique and this is especially useful when not a priori hypothesis is made, and the researcher must understand the relationship between factors and measured variables (Finch & West 1997). In the following section, you will see an explanation of the use of Exploratory Factor Analysis.

4.2.1 Exploratory Factor Analysis

According to (Brown 2015), Exploratory Factor Analysis (EFA) is a data-driven approach, such that no specifications are made regarding the number of factors (initially) or the pattern of relationships between the common factors and the indicators (i.e., the factor loadings). In other words, EFA is a statistical technique that is used to identify the latent relational structure among a set of variables and narrow down to a smaller number of variables. This essentially means that the variance of a large number of variables can be described by a few summary variables (Preetish 2017). It is commonly employed by researchers as an exploratory or descriptive technique to determine the appropriate number of common factors, and to uncover which **measured variables** are reasonable indicators of the various **latent dimensions** (e.g., by the size and differential magnitude of factor loading) (Norris & Lecavalier 2010; Brown 2015). It should be used when the researcher does not have a priori hypothesis about factors or patterns of measured variables as mentioned in the section above (Finch & West 1997). On the other hand, Confirmatory Factor Analysis (CFA), the researcher specifies the number of factors and the pattern of indicator factor loadings in advance, as well as other parameters such as those bearing on the independence or covariance of the factors and indicator unique variances (Brown 2015). The pre-specified factor solution is evaluated in terms of how well it reproduces the sable correlation (covariance) matrix of the measured variables. In such a way, dissimilar to EFA, CFA needs a strong empirical or conceptual foundation to guide the specification and evaluation of the factor model (Norris & Lecavalier 2010). Subsequently, EFA is frequently used earlier in the process of scale development and construct validation, while CFA is used in later phases after

the elemental structure has been well-established on prior empirical (EFA) and theoretical grounds. In Figure 12 below you will find an overview of exploratory factor analysis:

Figure 11: Overview of exploratory factor analysis. "v" stands for variables.



4.2.2 Procedures of EFA

According to (Brown 2015), EFA is an "exploratory" analysis because not a priori restriction is placed on the pattern of relationships between the observed measures and the latent variables. This are the key differences between EFA and CFA.

This thesis followed the process of (Brown 2015), after determining that EFA is the most appropriate analytic technique for empirical question at hand; the researcher must decide which indicators to include in the analysis and determine if the size and the nature of the sample are suitable for the analysis. Typically, the process steps to follow on EFA include:

1. Selection of a specific method to estimate the factor model;

2. Selection of the appropriate number of factors;

3. In the case of models that have more than one factor, selection of a technique to rotate the initial factor matrix to foster the interpretability of the solution; and

4. If desired, the selection of a method to compute factor scores.

The process steps are summarized in the table below:

Table 16: Fundamental Steps and Procedural Recommendation for EFA (Brown 2015)

Factor extraction **Use an estimator based on the common factor model, such as:** ***Principal factors:*** No distributional assumptions; less prone to improper solutions than maximum likelihood. ***Maximum likelihood:*** Assumes multivariate normality, but provides goodness-of-fit evaluation and, in some cases, significant tests and confident intervals of parameter estimates**.**
Factor selection **Determine the appropriate number of factors by:** *Scree plot* of eigenvalues from the reduced correlation matrix, *Parallel analysis*, and/or *Goodness of model fit* (e.g., RMSEA, x^2)
Factor rotation **In multicultural models, rotate the solution to obtain a simple structure by**: Using an oblique rotation method (e.g., promax, geomin)
Interpret the factors and evaluate the quality of the solution **Consider the meaningfulness and interpretability of the factors:** Factors should have substantive meaning and conceptual/empirical relevance Rule out no substantive explanations such as method effects (e.g., factors composed of reverse and non-reverse worded items) **Eliminate poorly defined factors, such as:**

Factors on which only two or three items have salient loadings. Factors defined by items that have small loadings (*i.e., low communalities*) Factors with *low factor determinacy* (poor correspondence between the factors and their factor scores.) **Eliminate poorly behaved items (indicators), such as:** Items with high loading on more than one factor (*i.e., cross-loading*) Items with small loadings on all factors (*i.e., low communalities*)
<u>Re-run and (ideally) replicate the factor analysis</u> **If items or factors are dropped in preceding steps rerun the EFA in the same sample.** **Replicate the final EFA solution in an independent sample** **Consider further replications/extensions of the factor solution by:** Developing tentative CFA models (e.g., exploratory SEM) Larger-scale CFA investigations Measurement invariance evaluation in population subgroups (e.g., equivalence of solution between sexes)

Note: EFA, exploratory factor analysis; RMSEA, root mean square error of approximation; CFA, confirmatory factor analysis; SEM, structural equation modeling.

4.2.3 Details

To carry out the Exploratory Factor Analysis, we used the statistical software R, already popular in research and providing this statistical analysis. The questionnaire answers collected from "Google Forms" were downloaded in CSV format into Excel and manually checked for errors. There, we reshaped the answers data in a common format used by R. After, the data was uploaded into "R" and stored for analysis.

4.2.4 Factor Extraction

There are many methods that can be used to estimate the common factor model, such as maximum likelihood (ML), principal factors (PL), weighted least squares, unweighted least squares, generalized least squares, imaging analysis, minimum residual analysis, and alpha factoring, to name just some (Brown 2015). For EFA, the most frequently used factor extraction methods are ML and PL. In our analysis, we used the classic ML procedure.

4.2.5 Factor Selection (Number of Factors)

The first question to answer in our study is to find the factors. The question is looking for how many factors we need to explain the variability of the data and then the adoption of big data analytics. While there is not a definite clear answer coming from the statistical approach, different methods are available to understand what a good number is.

This can be evaluated via some methods such as Scree plot of eigenvalues, Parallel Analysis, and/or Goodness of model fit as mentioned before in Table 15 above.

This study used "Parallel Analysis" method. This method is an eigenvalue-based procedure for guiding factor selection (Humphreys & Montanelli 1975). The approach is based on a scree plot of the eigenvalues obtained from the sample data against eigenvalues that are estimated from a data set of random numbers. According to (Brown 2015), both the observed sample and random data eigenvalues are plotted, and the appropriate number of factors is indicated by the point where the two lines cross. So, the factor selection is guided by the number of real eigenvalues greater than the eigenvalues generated from the random data; that is, if the "real" factor explains less variance than the corresponding factor obtained from the random numbers, it should not be included in the factor analysis. The term parallel analysis refers to the fact that the random data sets should have a parallel aspect of the actual research data. (Brown 2015)

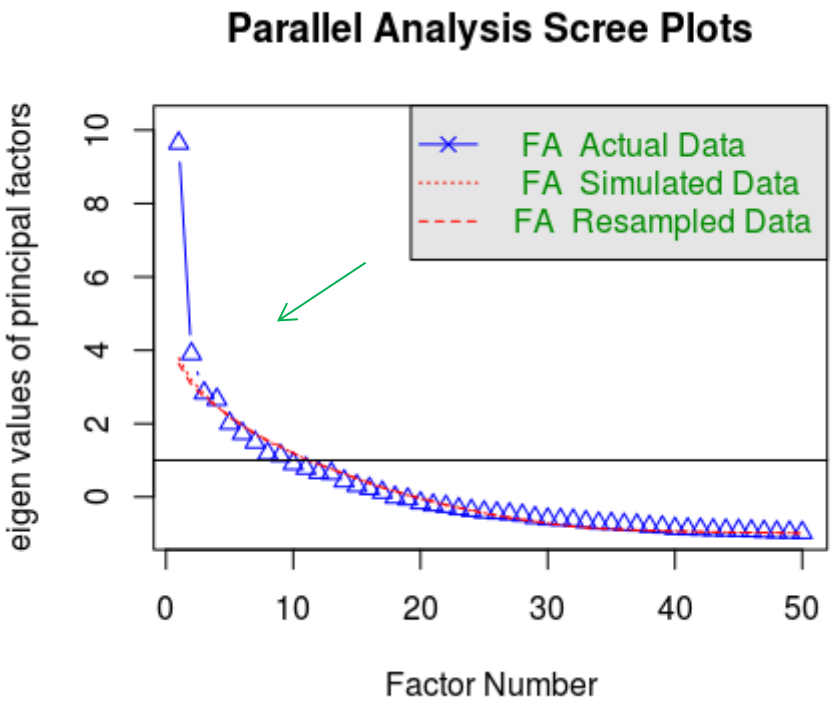
To summarize, the scree plot associated with my parallel analysis shows the eigenvalues variation as a function of the number of chosen factors. It indicates the explanatory power of the model depending on how many factors we use to describe the data. More precisely, what is shown is related to the remaining variability that we need to explain using N factors. As you can see, the function plotted is decreasing, indicating that more factors explain better the collected data that will be. However, this study is not interested in taking as many factors as possible, otherwise, we will end up having one factor per variable, and this is not our objective. The objective is to find a good tradeoff between data explanation and variables 'summarization' in the form of broad concepts/factors. A common method to choose this tradeoff is to take a sharp decrease in the scree plot (the 'elbow method') as a threshold to choose the number of factors.

This research used R that is a language and environment for statistical computing and graphics. R provides a wide variety of statistical (linear and nonlinear modeling, classical statistical tests, time-series analysis, classification, clustering, etc.) and graphical techniques, and is highly extensible. This free software is widely used among statisticians and data miners for developing statistical software and data analysis (The R Foundation for Statistical Computing 2018.) Thus, this study used "Psych" package's "fa.parallel" function on "R" to execute a parallel analysis.

4.3 Results

Now that a simple structure is achieved, it is time to validate the model. Let's look at the factor analysis output to proceed to validate the model. In Figure 12 you will see the "scree plot" below.

Figure 12: Parallel Analysis Screen Plots to validate the model. Source: Author



The blue line shows eigenvalues of actual data and the two red lines (placed on top of each other) show simulated and resampled data. Here we can see on the large drops the actual data and on the spots the point in where it levels off to the right. Also, the point of inflection was located that is the point where the gap between the simulated data and actual data tends to be minimum.

Looking at this plot and parallel analysis, anywhere between 3 to 10 factors would be a good choice.

4.3.1 Factor Rotation

According to (Brown 2015) "Once the appropriate number of factors has been determined, the extracted factors are rotated, to foster their interpretability. In instances when two or more factors are involved, rotation is relevant because of the indeterminate nature of the common factor model. That is, for any given multiple-factor model, there is an infinite number of equally good-fitting solution."

There are two major types of rotation: **orthogonal** and **oblique**. In **orthogonal rotation**, the factors are constrained to be uncorrelated; in **oblique rotation**, the factors can intercorrelate. The correlation between the two factors is equal to the cosine of the

angle between the rotational axes. Because cos (90º) =0, the factors are uncorrelated in orthogonal rotation. In oblique rotations, the angle of the axis can be greater or less than 90º, and thus the cosine of the angle may yield a factor correlation between zero and one (Rahn 2018).

In my case, I made factor rotation "Oblimin" (**oblique rotation)** and "Varimax" (**orthogonal rotation)** that allowed me either uncorrelated or correlated factors as shown in Figure 13-14. The results did not change fundamentally as you will see in the Parallel Analysis shown in Figure 15.

Figure 13: Correlation for the non - binary. Source: Author

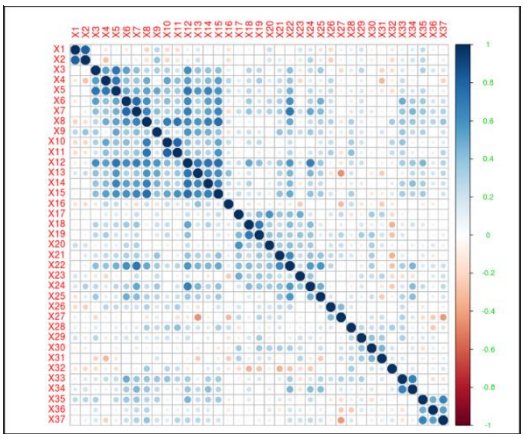


Figure 14: All variables. Source: Author

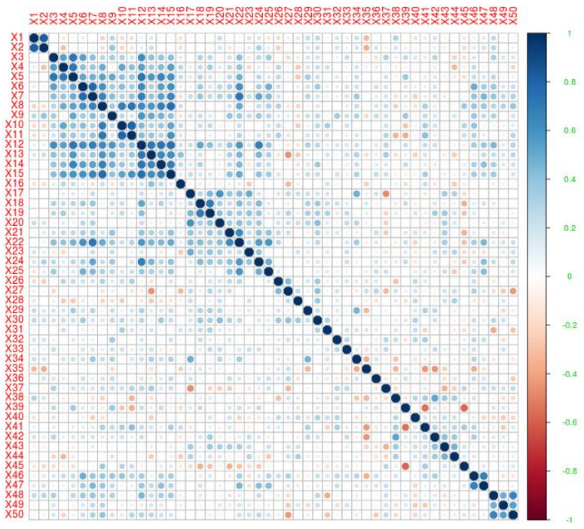
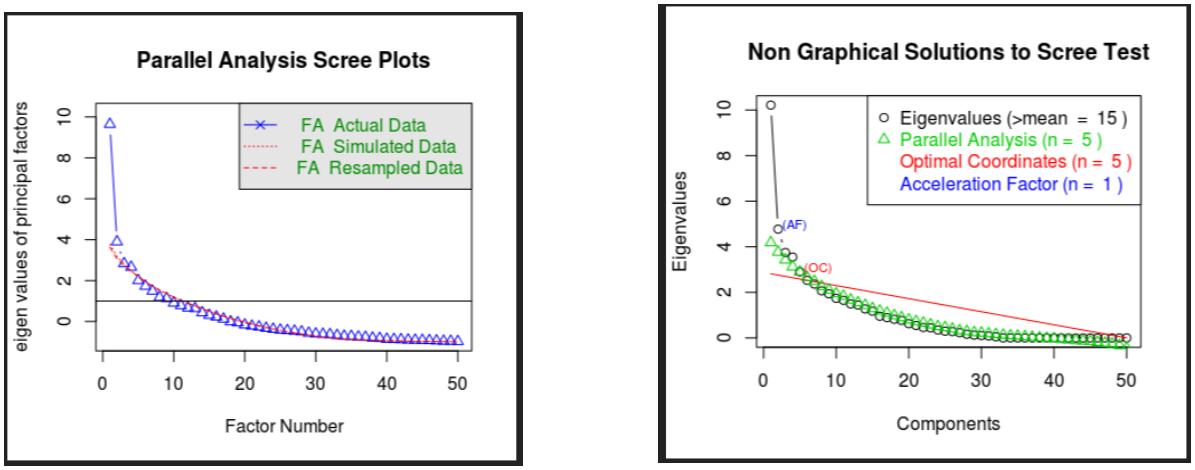


Figure 15: Parallel Analysis. The results did not change fundamentally. Source: Author



4.3.2 Interpret the factors and evaluate the quality of the solution

Now that the probable number of factors is set, let`s start off the analysis with three (3) as the number of factors. In order to perform factor analysis, as I mentioned before this research used "psych" package's on "R" using the fa() function. The arguments used in this study are shown below:

- r – Raw data or correlation or covariance matrix.
- n factors-Number of factors to extract.
- rotate -Although there are various types of rotation as mentioned before in Table 15. "Varimax" and "Oblimin" are the most popular.
- fm- One of the factor extraction techniques mentioned before in Table 15. (e.g. "Minimum Residual" (OLS), "Maximum Likelihood", "Principal Factors" etc.). This analysis used "Maximum Likelihood"

This analysis selected oblique rotation (rotate = "oblimin") as we believe that there is a correlation in the factors. Note that Varimax rotation is used under the assumption that the factors are completely uncorrelated. We used `Ordinary Least Squared/Minres` factoring (fm = "minres"), as it is known to provide results similar to `Maximum Likelihood` without assuming a multivariate normal distribution and derives solutions through iterative eigendecomposition like principal axis.

4.3.3 Adequacy Test with three (3) factors

Now that it is achieved simple structure it's time to validate the model. Let's look at the factor analysis output to proceed. In Figure 16 and Figure 17 is the output showing factors and loadings got in "R".

The root mean square of residuals (RMSR) is 0.12. This is acceptable as this value should be closer to 0. Next, we should check RMSEA (root mean square error of approximation) index. Its value, 0.587 did not show a good model fit as isn't below

0.05. Finally, the Tucker-Lewis Index (TLI) is -0.119 which is not an acceptable value considering it isn't over 0.9.

Figure 16: "R" Screenshot. Output loadings with three (3) factors. Source: Author

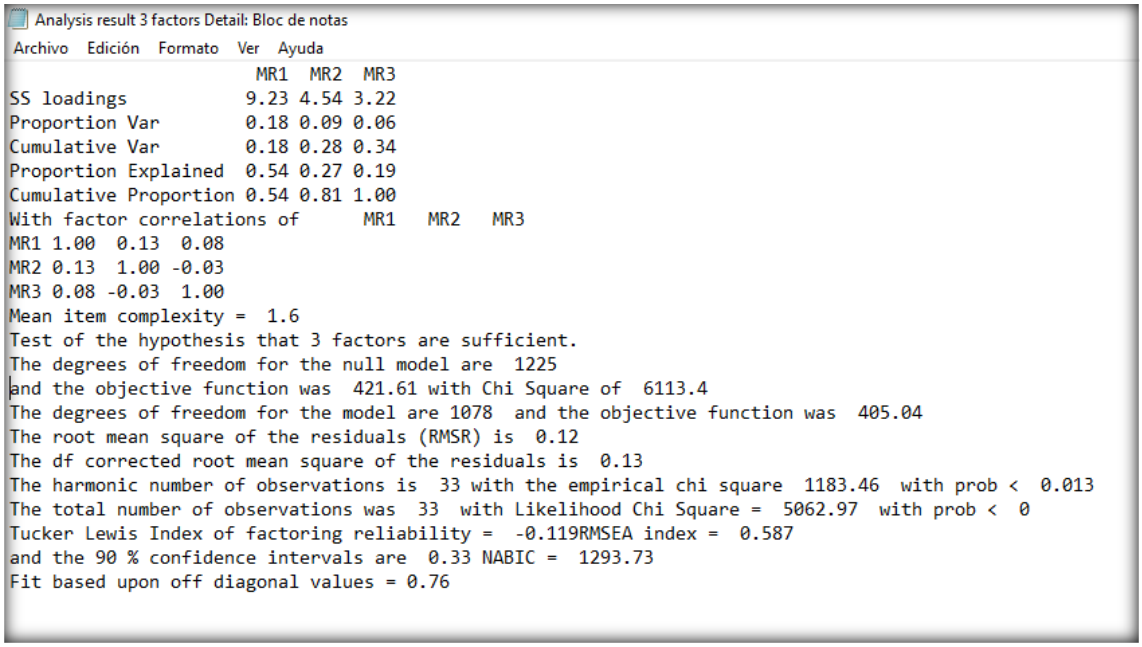


Figure 17: Excel Screenshot. Output showing factors and loadings. Original Research. Source: Author

Column1	Column2	Column3	Column4
	MR1	MR2	MR3
Age	-0.0525466676	0.2703391889	0.1200733247
Years.of.Experience	0.0139544763	0.2741446064	0.0595113238
Influence.of.SSCA.within.10.years	0.5909204735	0.041992988	-0.0047903315
Importance.of.Number.and.size.of.resources.owned	0.5888309615	-0.0008518279	-0.0561373922
Importance.of.Fitness.of.resources.owned	0.7463678789	0.0495437235	-0.0788842646
Importance.of.IT.systems.implemented	0.7097810458	0.1375573723	0.0977463845
Importance.of.Automatic.identification.systems.and.data.interchange.systems	0.7376291962	0.2296485654	-0.0002346756
Importance.of.resources.layout..allocation.and.availability.	0.8603704599	-0.2707360985	0.0947113617
Intangible.Assets..Competitive.position.	0.5054296265	0.2526633907	0.1327740594
Intangible.Assets..Range.of.the.offer.	0.5935032133	-0.2346756695	0.2700717645
Intangible.Assets..Territorial.scope.of.business.activity.	0.6147637673	-0.2921304129	0.2014870689
Intangible.Assets..Flexibility.of.operation.and.innovation.transfer.	0.8824440732	0.1975773309	-0.0370708875
Intangible.Assets..Organizational.maturity.	0.7565113681	-0.1073953006	-0.1989934701
Intangible.Assets..Organization.culture.	0.7395686378	0.0108985141	-0.0148055182
Intangible.Assets..Efficiency.at.operational.level.	0.8306543375	-0.0453811738	0.074220479
Intangible.Assets..Other..please.specify.below...	0.2413928026	-0.2160383453	-0.0158010251
Importance.of.commitment.from.management.to.achieve.sustainability	0.0505582527	0.6552033916	-0.0972599949
Importance.of.for.top.management.to.avoid.greenwash	0.3046580022	0.4835319148	-0.0214942942
Importance.of.governmental.regulations	0.1317017894	0.6399733086	0.1920156517
Importance.of.the.cost.of.implementing.green.logistics	0.0884317109	0.6027497205	-0.023272017
Importance.of.international.agreements	0.3085978616	0.4883381054	0.0005124475
Importance.of.information.and.business.analytics.create.a.competitive.advantage	0.639296513	0.4368860472	-0.1058056658
Impact.of.domestic.and.environmental.policies	-0.0302734453	0.5062501689	-0.0493706796
Importance.of.customers.awareness	0.4745669269	0.3989248616	-0.1433384457
impact..of.big.data.tools.for.sustainability.	0.446536928	0.0868609987	0.0736551218
How.has.your.access.to.useful.data.changed.during.the.past.year.....	0.1912900777	0.1489775302	0.1253570005
How.often.do.you.feel.you.have.the.right.data.needed.to.make.key.business.decisions.....	-0.2291999222	0.465199528	0.2578551733
Data.is.timely	-0.2783522136	0.2879311893	0.2253382387
Data.is.Relevant	0.2058082858	0.2162080486	0.2428054964
Data.is.Reliable	0.2420561684	0.4010978184	0.1861619588
Data.is.Accessible	0.0918431012	0.1739508392	-0.0699921111
Data.is.Consistent	0.0915608304	0.0800193353	0.3729539871
Data.is.Complete	0.1893652274	0.09560096	0.1909905264
just.began.to.apply.analytics	0.2677877617	0.1937311829	0.0176485358
aren.t.sure	-0.0507159427	0.0032908428	-0.4161321873
haven.t.acted	0.157949889	0.1318396999	-0.1406762192
do.not.use.analytics.to.drive.strategic.decisions.	0.3967169196	-0.4323465828	-0.0132540043
We.are.using.analytics..but.so.are.our.competitors.	-0.2304356761	0.1905401129	0.5716925129
Analytics.is.not.a.priority.for.senior.management.	0.1098770967	0.3729282751	-0.462736703
Staff.doing.the.input.need.to.know.more.about.the.end.results	-0.1449369231	0.1204940073	0.4225911633
Analytics.help.improving.innovation	0.2394578067	-0.1721357305	0.7109079771
Your.organization.uses.customer.feedback.to.inform.decision.making	0.0939113592	0.2168163506	0.4724104778
Use.of.detailed.data.to.tailor.specific.offerings.to.customers	-0.1108359878	0.3948463077	0.4335940556
Customers.are.engaged.with.your.organization	-0.2236079605	0.325129659	0.4537257505
Customer.intelligence.has.improved.since.last.year	0.0534884685	-0.4535989488	0.4105101402
Effectiveness.of.lean.processes.and.cutting.of.wastes	0.3835364421	0.0909760416	0.4399564393
Green.Purchasing.helps.sustainability	0.392222807	0.0664220085	0.1436628628
Would.you.....use.BDPA.to.turn.your.purchasing.more.green.or.sustainable..	0.3776505937	0.0177466166	-0.1007903073
Would.you.....implement.BDPA.if.it.could.improve.your.purchasing..	0.2301990145	-0.0291135058	-0.2374289225
Would.you.....implement.BDPA.if.it.could.make.your.company.more.green..	0.3464263611	-0.1516438773	-0.1069844006

Factors

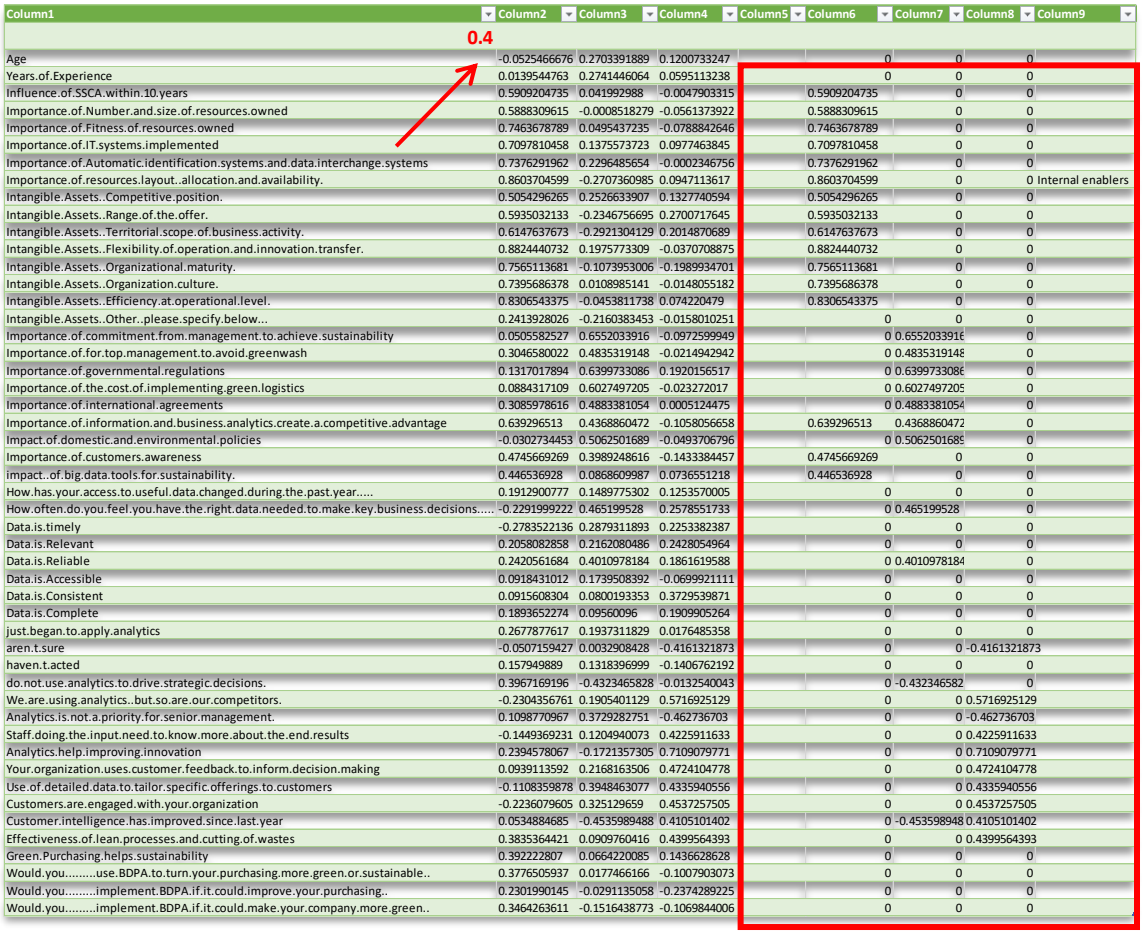
Loadings

Note: For better understanding, these results will be also in Annex b.

Now I need to consider the loadings more than **0.4** and not loading on more than one factor. Note that negative values are acceptable here. So, let's first establish the cut off to improve visibility as shown in the Screenshot of Figure 18 below (It's also shown in Annex b):

- print (three factors loadings, cutoff = 0.4

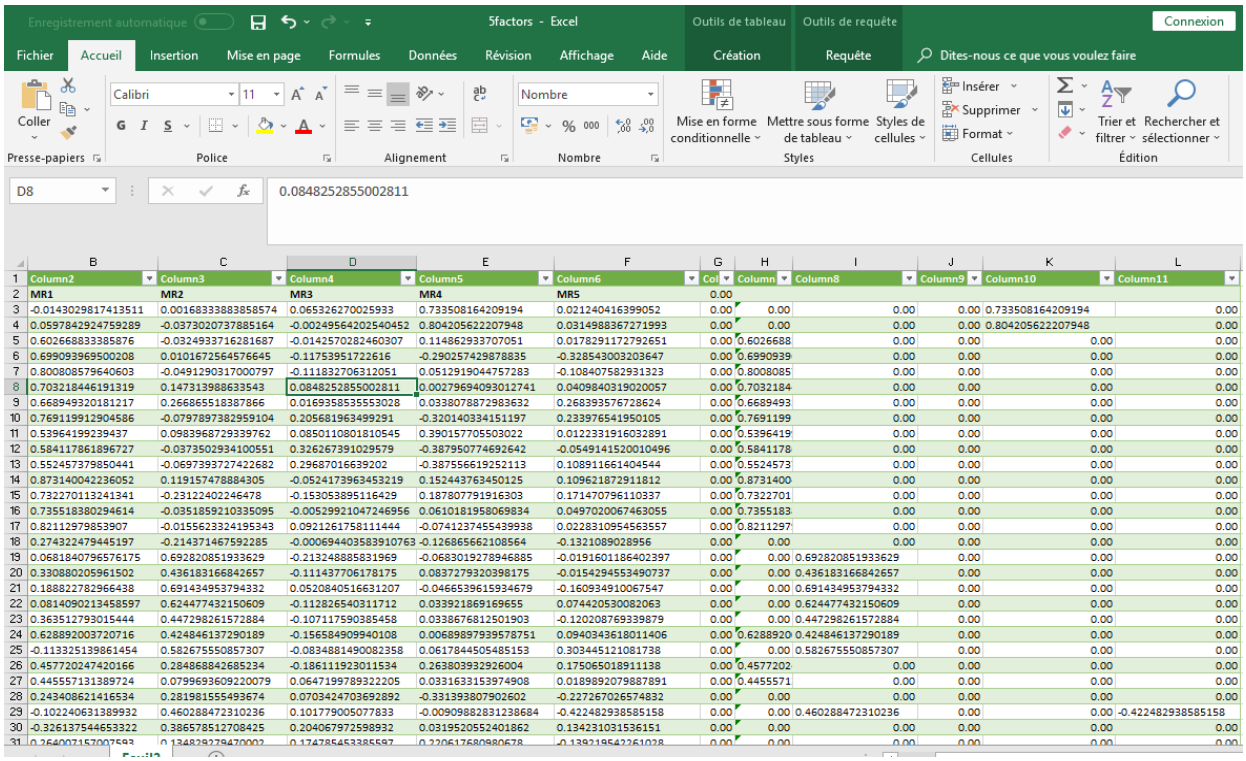
Figure 18: Excel Screenshot. Output showing (3) factors and loadings considering loadings more than 0.4. Source: Author



Column1	Column2	Column3	Column4	Column5	Column6	Column7	Column8	Column9
	0.4							
Age	-0.0525466676	0.2703391889	0.1200733247		0	0	0	
Years.of.Experience	0.0139544763	0.2741446064	0.0595113238		0	0	0	
Influence.of.SSCA.within.10.years	0.5909204735	0.041992988	-0.0047903315		0.5909204735	0	0	
Importance.of.Number.and.size.of.resources.owned	0.5888309615	-0.0008518279	-0.0561373922		0.5888309615	0	0	
Importance.of.Fitness.of.resources.owned	0.7463678789	0.0495437235	-0.0788842646		0.7463678789	0	0	
Importance.of.IT.systems.implemented	0.7097810458	0.1375573723	0.0977463845		0.7097810458	0	0	
Importance.of.Automatic.identification.systems.and.data.interchange.systems	0.7376291962	0.2296485654	-0.0002346756		0.7376291962	0	0	
Importance.of.resources.layout..allocation.and.availability.	0.8603704599	-0.2707360985	0.0947113617		0.8603704599	0	0	Internal enablers
Intangible.Assets..Competitive.position.	0.5054296265	0.2526633907	0.1327740594		0.5054296265	0	0	
Intangible.Assets..Range.of.the.offer.	0.5935032133	-0.2346756695	0.2700717645		0.5935032133	0	0	
Intangible.Assets..Territorial.scope.of.business.activity.	0.6147637673	-0.2921304129	0.2014870689		0.6147637673	0	0	
Intangible.Assets..Flexibility.of.operation.and.innovation.transfer.	0.8824440732	0.1975773309	-0.0370708875		0.8824440732	0	0	
Intangible.Assets..Organizational.maturity.	0.7565113681	-0.1073953006	-0.1989934701		0.7565113681	0	0	
Intangible.Assets..Organization.culture.	0.7395686378	0.0108985141	-0.0148055182		0.7395686378	0	0	
Intangible.Assets..Efficiency.at.operational.level.	0.8306543375	-0.0453811738	0.074220479		0.8306543375	0	0	
Intangible.Assets..Other..please.specify.below...	0.2413928026	-0.2160383453	-0.0158010251		0	0	0	
Importance.of.commitment.from.management.to.achieve.sustainability	0.0505582527	0.6552033916	-0.0972599949		0	0.655203391	0	
Importance.of.for.top.management.to.avoid.greenwash	0.3046580022	0.4835319148	-0.0214942942		0	0.4835319148	0	
Importance.of.governmental.regulations	0.1317017894	0.6399733086	0.1920156517		0	0.639973308	0	
Importance.of.the.cost.of.implementing.green.logistics	0.0884317109	0.6027497205	-0.023272017		0	0.602749720	0	
Importance.of.international.agreements	0.3085978616	0.4883381054	0.0005124475		0	0.488338105	0	
Importance.of.information.and.business.analytics.create.a.competitive.advantage	0.639296513	0.4368860472	-0.1058056658		0.639296513	0.436886047	0	
Impact.of.domestic.and.environmental.policies	-0.0302734453	0.5062501689	-0.0493706796		0	0.506250168	0	
Importance.of.customers.awareness	0.4745669269	0.3989248616	-0.1433384457		0.4745669269	0	0	
impact..of.big.data.tools.for.sustainability.	0.446536928	0.0868609987	0.0736551218		0.446536928	0	0	
How.has.your.access.to.useful.data.changed.during.the.past.year.....	0.1912900777	0.1489775302	0.1253570005		0	0	0	
How.often.do.you.feel.you.have.the.right.data.needed.to.make.key.business.decisions.....	-0.2291999222	0.465199528	0.2578551733		0	0.465199528	0	
Data.is.timely	-0.2783522136	0.2879311893	0.2253382387		0	0	0	
Data.is.Relevant	0.2058082858	0.2162080486	0.2428054964		0	0	0	
Data.is.Reliable	0.2420561684	0.4010978184	0.1861619588		0	0.401097818	0	
Data.is.Accessible	0.0918431012	0.1739508392	-0.0699921111		0	0	0	
Data.is.Consistent	0.0915608304	0.0800193353	0.3729539871		0	0	0	
Data.is.Complete	0.1893652274	0.09560096	0.1909905264		0	0	0	
just.began.to.apply.analytics	0.2677877617	0.1937311829	0.0176485358		0	0	0	
aren.t.sure	-0.0507159427	0.0032908428	-0.4161321873		0	0	-0.4161321873	
haven.t.acted	0.157949889	0.1318396999	-0.1406762192		0	0	0	
do.not.use.analytics.to.drive.strategic.decisions.	0.3967169196	-0.4323465828	-0.0132540043		0	-0.432346582	0	
We.are.using.analytics..but.so.are.our.competitors.	-0.2304356761	0.1905401129	0.5716925129		0	0	0.5716925129	
Analytics.is.not.a.priority.for.senior.management.	0.1098770967	0.3729282751	-0.462736703		0	0	-0.462736703	
Staff.doing.the.input.need.to.know.more.about.the.end.results	-0.1449369231	0.1204940073	0.4225911633		0	0	0.4225911633	
Analytics.help.improving.innovation	0.2394578067	-0.1721357305	0.7109079771		0	0	0.7109079771	
Your.organization.uses.customer.feedback.to.inform.decision.making	0.0939113592	0.2168163506	0.4724104778		0	0	0.4724104778	
Use.of.detailed.data.to.tailor.specific.offerings.to.customers	-0.1108359878	0.3948463077	0.4335940556		0	0	0.4335940556	
Customers.are.engaged.with.your.organization	-0.2236079605	0.325129659	0.4537257505		0	0	0.4537257505	
Customer.intelligence.has.improved.since.last.year	0.0534884685	-0.4535989488	0.4105101402		0	-0.453598948	0.4105101402	
Effectiveness.of.lean.processes.and.cutting.of.wastes	0.3835364421	0.0909760416	0.4399564393		0	0	0.4399564393	
Green.Purchasing.helps.sustainability	0.392222807	0.0664220085	0.1436628628		0	0	0	
Would.you.....use.BDPA.to.turn.your.purchasing.more.green.or.sustainable..	0.3776505937	0.0177466166	-0.1007903073		0	0	0	
Would.you.....implement.BDPA.if.it.could.improve.your.purchasing..	0.2301990145	-0.0291135058	-0.2374289225		0	0	0	
Would.you.....implement.BDPA.if.it.could.make.your.company.more.green..	0.3464263611	-0.1516438773	-0.1069844006		0	0	0	

As you can see some variables have become insignificant and others have double-loading. Next, **we considered "5" factors**. You can see on these results that it is only a single loading as shown in Figure 19 below. This is known as simple structural equation modeling (SEM), and according to this, it includes a diverse set of mathematical models, computer algorithms, and statistical methods that fit networks of constructs to data (Kaplan 2001). SEM also includes confirmatory factor analysis, path analysis, partial least squares path modeling, and latent growth modeling. SEM is often used to assess unobservable 'latent' constructs. They often invoke a measurement model that defines latent variables using one or more observed variables, and a structural model that imputes relationships between latent variables (Kaplan 2009; Kline 2011). For better understanding, these results will be available also in Annex b.

Figure 19: Excel screenshot. Output showing (5) factors and loadings considering loadings more than 0.4. Source: Author

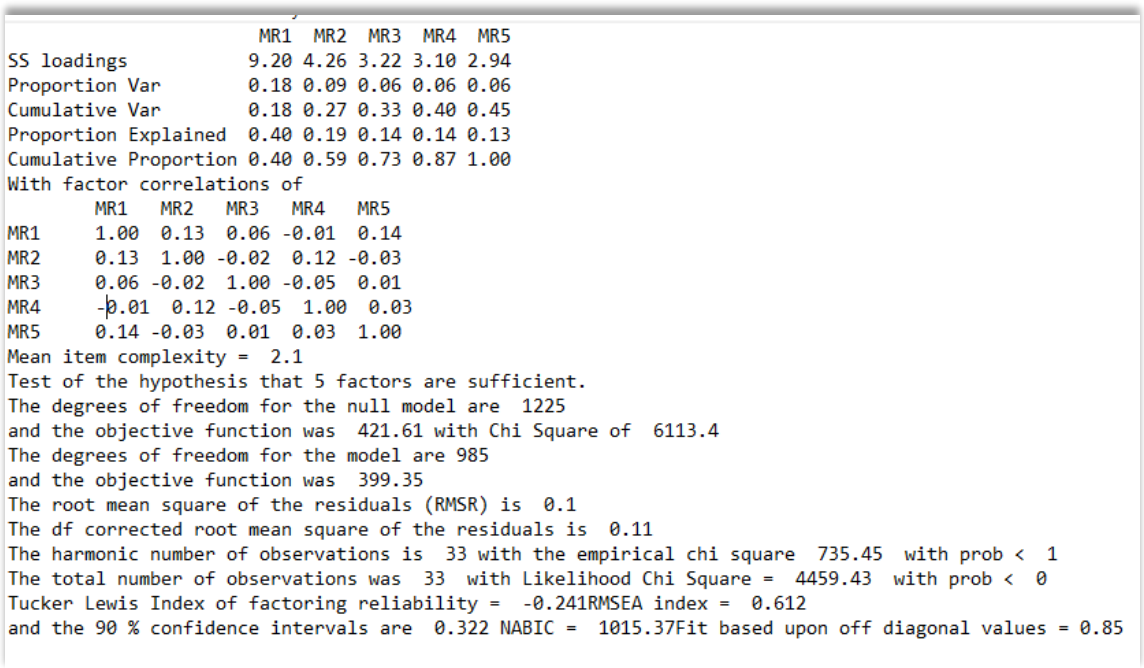


	B	C	D	E	F	G	H	I	J	K	L
1	Column2	Column3	Column4	Column5	Column6	Co	Column	Column8	Column9	Column10	Column11
2	MR1	MR2	MR3	MR4	MR5	0.00					
3	-0.0143029817413511	0.00168333883858574	0.065326270025933	0.733508164209194	0.021240416399052	0.00	0.00	0.00	0.00	0.733508164209194	0.00
4	0.0597842924759289	-0.0373020737885164	-0.00249564202540452	0.804205622207948	0.0314988367271993	0.00	0.00	0.00	0.00	0.804205622207948	0.00
5	0.602668833385876	-0.0324933716281687	-0.0142570282460307	0.114862933707051	0.0178291172792651	0.00	0.6026688	0.00	0.00	0.00	0.00
6	0.699093969500208	0.0101672564576645	-0.11753951722616	-0.290257429878835	-0.328543003203647	0.00	0.6990939	0.00	0.00	0.00	0.00
7	0.800808579640603	-0.0491290317000797	-0.111832706312051	0.0512919044757283	-0.108407582931323	0.00	0.8008085	0.00	0.00	0.00	0.00
8	0.703218446191319	0.147313988633543	0.0848252855002811	0.00279694093012741	0.0409840319020057	0.00	0.7032184	0.00	0.00	0.00	0.00
9	0.668949320181217	0.266865518387866	0.0169358535553028	0.0338078872983632	0.268393576728624	0.00	0.6689493	0.00	0.00	0.00	0.00
10	0.769119912904586	-0.0797897382959104	0.205681963499291	-0.320140334151197	0.233976541950105	0.00	0.7691199	0.00	0.00	0.00	0.00
11	0.53964199239437	0.0983968729339762	0.0850110801810545	0.390157705503022	0.0122331916032891	0.00	0.5396419	0.00	0.00	0.00	0.00
12	0.584117861896727	-0.0373502934100551	0.326267391029579	-0.387950774692642	-0.0549141520010496	0.00	0.5841178	0.00	0.00	0.00	0.00
13	0.552457379850441	-0.0697393727422682	0.29687016639202	-0.387556619252113	0.108911661404544	0.00	0.5524573	0.00	0.00	0.00	0.00
14	0.873140042236052	0.119157478884305	-0.0524173963453219	0.152443763450125	0.109621872911812	0.00	0.8731400	0.00	0.00	0.00	0.00
15	0.732270113241341	-0.23122402246478	-0.153053895116429	0.187807791916303	0.171470796110337	0.00	0.7322701	0.00	0.00	0.00	0.00
16	0.735518380294614	-0.0351859210335095	-0.00529921047246956	0.0610181958069834	0.0497020067463055	0.00	0.7355183	0.00	0.00	0.00	0.00
17	0.82112979853907	-0.0155623324195343	0.0921261758111444	-0.0741237455439938	0.0228310954563557	0.00	0.8211297	0.00	0.00	0.00	0.00
18	0.274322479445197	-0.214371467592285	-0.000694403583910763	-0.126865662108564	-0.1321089028956	0.00	0.00	0.00	0.00	0.00	0.00
19	0.0681840796576175	0.692820851933629	-0.213248885831969	-0.0683019278946885	-0.0191601186402397	0.00	0.00	0.692820851933629	0.00	0.00	0.00
20	0.330880205961502	0.436183166842657	-0.111437706178175	0.0837279320398175	-0.0154294553490737	0.00	0.00	0.436183166842657	0.00	0.00	0.00
21	0.188822782966438	0.691434953794332	0.0520840516631207	-0.0466539615934679	-0.160934910067547	0.00	0.00	0.691434953794332	0.00	0.00	0.00
22	0.0814090213458597	0.624477432150609	-0.112826540311712	0.033921869169655	0.074420530082063	0.00	0.00	0.624477432150609	0.00	0.00	0.00
23	0.363512793015444	0.447298261572884	-0.107117590385458	0.0338676812501903	-0.120208769339879	0.00	0.00	0.447298261572884	0.00	0.00	0.00
24	0.628892003720716	0.424846137290189	-0.156584909940108	0.00689897939578751	0.0940343618011406	0.00	0.6288920	0.424846137290189	0.00	0.00	0.00
25	-0.113325139861454	0.582675550857307	-0.0834881490082358	0.0617844505485153	0.303445121081738	0.00	0.00	0.582675550857307	0.00	0.00	0.00
26	0.457720247420166	0.284868842685234	-0.186111923011534	0.263803932926004	0.175065018911138	0.00	0.4577202	0.00	0.00	0.00	0.00
27	0.445557131389724	0.0799693609220079	0.0647199789322205	0.0331633153974908	0.0189892079887891	0.00	0.4455571	0.00	0.00	0.00	0.00
28	0.243408621416534	0.281981555493674	0.0703424703692892	-0.331393807902602	-0.227267026574832	0.00	0.00	0.00	0.00	0.00	0.00
29	-0.102240631389932	0.460288472310236	0.101779005077833	-0.00909882831238684	-0.422482938585158	0.00	0.00	0.460288472310236	0.00	0.00	-0.422482938585158
30	-0.326137544653322	0.386578512708425	0.204067972598932	0.0319520552401862	0.134231031536151	0.00	0.00	0.00	0.00	0.00	0.00
31	0.264007157007593	0.134829279470902	0.174785453385597	0.220617680980678	-0.139219542261028	0.00	0.00	0.00	0.00	0.00	0.00

4.3.4 Adequacy Test with five (5) factors

Now that it is achieved a simple structure with five (5) factors, it's time to validate the model. Let's look at the factor analysis output to proceed in Figure 20 below (also shown in Annex b):

Figure 20: ¨R¨ Screenshot. Output loadings with five (5) factors. Source: Author



```
                        MR1  MR2  MR3  MR4  MR5
SS loadings           9.20 4.26 3.22 3.10 2.94
Proportion Var        0.18 0.09 0.06 0.06 0.06
Cumulative Var        0.18 0.27 0.33 0.40 0.45
Proportion Explained  0.40 0.19 0.14 0.14 0.13
Cumulative Proportion 0.40 0.59 0.73 0.87 1.00
With factor correlations of
       MR1   MR2   MR3   MR4   MR5
MR1   1.00  0.13  0.06 -0.01  0.14
MR2   0.13  1.00 -0.02  0.12 -0.03
MR3   0.06 -0.02  1.00 -0.05  0.01
MR4   -0.01  0.12 -0.05  1.00  0.03
MR5   0.14 -0.03  0.01  0.03  1.00
Mean item complexity =  2.1
Test of the hypothesis that 5 factors are sufficient.
The degrees of freedom for the null model are  1225
and the objective function was  421.61 with Chi Square of  6113.4
The degrees of freedom for the model are 985
and the objective function was  399.35
The root mean square of the residuals (RMSR) is  0.1
The df corrected root mean square of the residuals is  0.11
The harmonic number of observations is  33 with the empirical chi square  735.45  with prob <  1
The total number of observations was  33  with Likelihood Chi Square =  4459.43  with prob <  0
Tucker Lewis Index of factoring reliability =  -0.241RMSEA index =  0.612
and the 90 % confidence intervals are  0.322 NABIC =  1015.37Fit based upon off diagonal values = 0.85
```

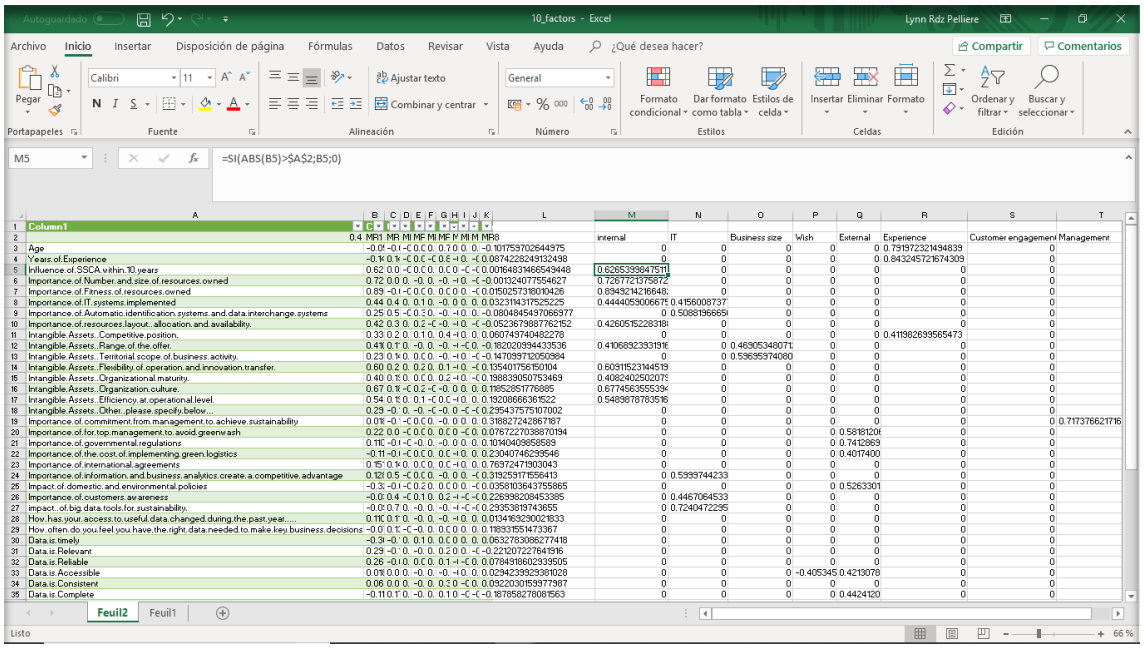
As you can see in Figure 20: The root mean square of residuals (RMSR) is 0.1. This is acceptable as this value should be closer to 0. Next, we should check RMSEA (root mean square error of approximation) index. Its value, 0.612 did not show a good model fit as isn't below 0.05. Finally, the Tucker-Lewis Index (TLI) is -0.241, it is not an acceptable value considering it isn't over 0.9.

The model with five (5) factors isn't good enough since there were not enough samples from the respondents. Thus now, it is necessary to make all the process that was made above trying now with ten (10) factors as you will see in Figure 21 and Figure 22 below:

Figure 21: ¨R¨ Screenshot. Output loadings with ten (10) factors. Source: Author

```
WARNING!!! MATRIX SINGULAR LOW PRECISION MAYBE TOO FEW DATA?
MR1  MR9  MR3  MR5  MR2  MR4 MR10  MR6  MR7  MR8SS
loadings              5.66 4.14 3.23 3.11 3.29 2.89 2.82 2.65 2.57 2.12
Proportion Var        0.11 0.08 0.06 0.06 0.07 0.06 0.06 0.05 0.05 0.04
Cumulative Var        0.11 0.20 0.26 0.32 0.39 0.45 0.50 0.56 0.61 0.65
Proportion Explained  0.17 0.13 0.10 0.10 0.10 0.09 0.09 0.08 0.08 0.07
Cumulative Proportion 0.17 0.30 0.40 0.50 0.60 0.69 0.77 0.86 0.93 1.00
With factor correlations of        MR1   MR9   MR3   MR5   MR2   MR4  MR10  MR6   MR7   MR8
MR1   1.00  0.36  0.15  0.12  0.20  0.06 -0.07 0.09 -0.06  0.05MR9   0.36  1.00  0.17  0.15  0.15  0.07 -0.02 0.14 -0.02  0.10
MR3   0.15  0.17  1.00  0.03 -0.03 -0.05  0.07 0.01 -0.05 -0.08MR5   0.12  0.15  0.03  1.00  0.10  0.04 -0.03 0.04 -0.10  0.02
MR2   0.20  0.15 -0.03  0.10  1.00  0.01  0.07 0.16  0.07  0.18MR4   0.06  0.07 -0.05  0.04  0.01  1.00  0.12 0.03 -0.04  0.01
MR10 -0.07 -0.02  0.07 -0.03  0.07  0.12  1.00 0.00  0.13  0.03MR6   0.09  0.14  0.01  0.04  0.16  0.03  0.00 1.00  0.05  0.13
MR7  -0.06 -0.02 -0.05 -0.10  0.07 -0.04  0.13 0.05  1.00  0.06MR8   0.05  0.10 -0.08  0.02  0.18  0.01  0.03 0.13  0.06  1.00
Mean item complexity =  3
Test of the hypothesis that 10 factors are sufficient.
The degrees of freedom for the null model are  1225  and the objective function was  421.61 with Chi Square of  6113.4
The degrees of freedom for the model are 770  and the objective function was  387.4
The root mean square of the residuals (RMSR) is  0.06
The df corrected root mean square of the residuals is  0.07
The harmonic number of observations is  33 with the empirical chi square  281.64  with prob <  1
The total number of observations was  33  with Likelihood Chi Square =  3034.66  with prob <  2.4e-265
Tucker Lewis Index of factoring reliability =  -0.734
RMSEA index =  0.687  and the 90 % confidence intervals are  0.292 NABIC =  342.35Fit based upon off diagonal values = 0.94
```

Figure 22: Excel screenshot. Output showing (10) factors and loadings considering loadings more than 0.4.



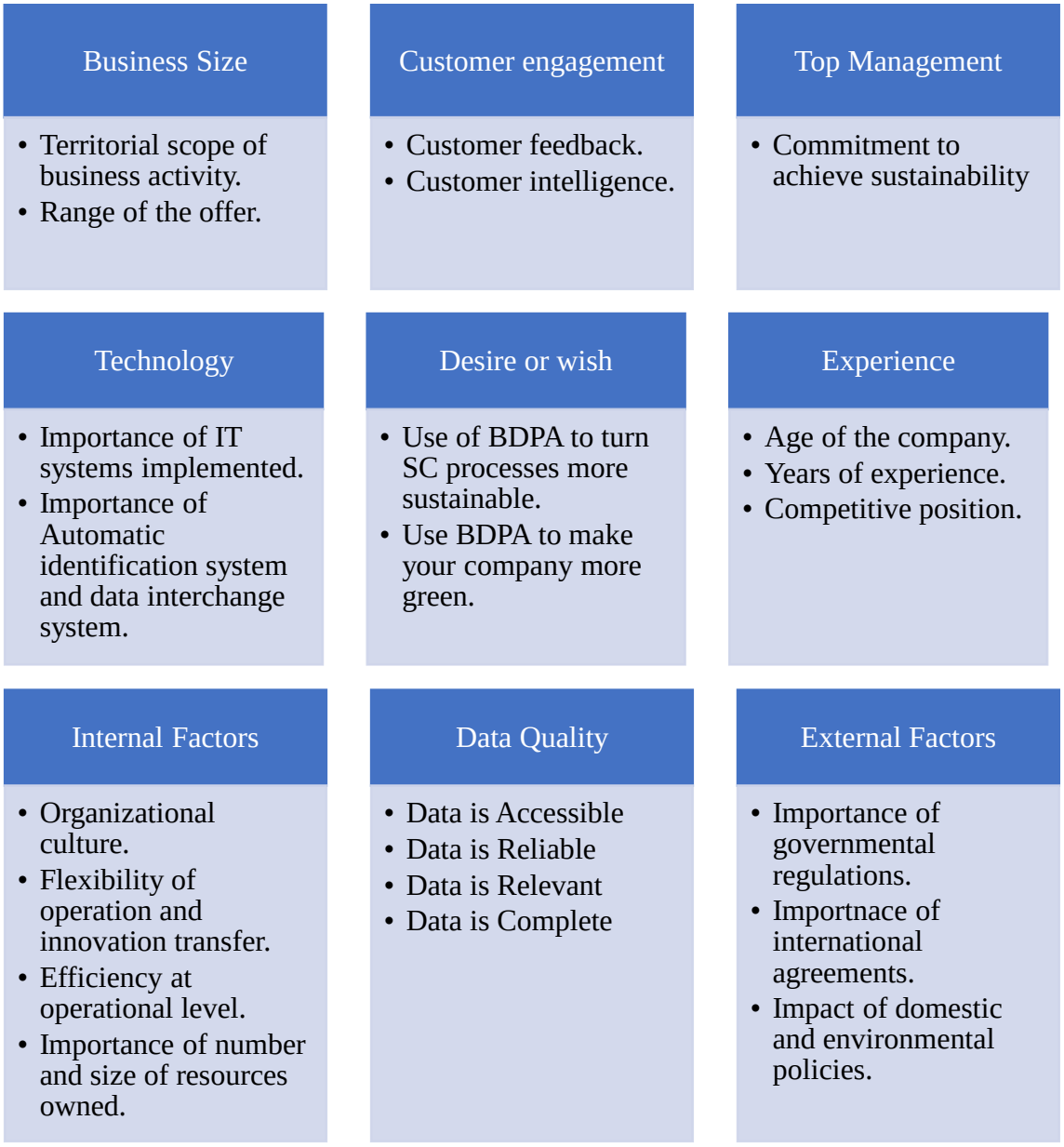
4.3.5 Adequacy Test with ten (10) factors

According to the results in Figure 21, the root mean square of residuals (RMSR) is 0.06. This is acceptable as this value should be closer to 0. Next, I should check RMSEA (root mean square error of approximation) index. Its value, 0.687 did not show a good model fit as isn't below 0.05. Finally, the Tucker-Lewis Index (TLI) is -0.734, it is not an acceptable value considering it isn't over 0.9.

4.3.6 Naming the Factors

After establishing the adequacy of the factors, it is time to name the factors found in the questionnaire. This is the theoretical side of the analysis where it forms the factors depending on the variable loadings got in the previous sections. In this case, Figure 23 shows how the factors can be created:

Figure 23: Factors found in the questionnaire depending on the variable loadings. Source: Author



4.4 Conclusions

This chapter wanted to explore the factors that affect the transformation of SSCA data in value. Thus, it had been discussed about the results gotten in this study from the

questionnaire developed using the basic idea of EFA, covered parallel analysis and scree plot interpretation. Then the research moved to factor analysis to achieve simple structure analysis and validate the same to ensure the model's adequacy. Later, the research arrived at the names of the factors from the variables. This research allows you to understand a better insight into the factors that can affect the adoption of big data on sustainable supply chain analytics. Based on the results that were run multiple times in EFA, this research did not find clear factors due to the few quantities of respondents. However, this research was capable to find the factors depending on the variable loadings that impact in the adoption of BDPA for SSCA, tools and techniques that enable decision making through SSCA, and the influence degree (coefficient 0.4 that was the relation between the question and the factor) of each factor for facilitating or delaying sustainability adoption that was not investigated before. The future research may focus on obtaining more inquests with more participants to be able to get a significant number of samples for a better statistical analysis.

Chapter Five: Case Study

5.1 Introduction

Case study has been used widely by researchers to develop and generate theories (Carter & Easton 2011.) The main reason for case study popularity in research is its ability to capture the dynamics and changes in the supply chain (Järvensivu & Törnroos 2010). In addition, big data applications on sustainable supply chain analytics are complex and require consideration of several contextual factors and settings (Firouzeh et al. 2017; Wang et al. 2016). One major reason for the great importance of the research process is the quality of research that is often flawed by a lack of rigor in the research process (Stuart et al. 2002.)

Spread of big data tools and techniques on sustainable supply chain analytics is a complex subject due to the internal and external enablers or factors that must be considered for understanding how BDPA tools and applications are adopted on sustainable supply chain analytics. The first research question in this thesis is concerned in explaining *What are the influence degrees of certain enablers that impact the effective implementation of BDPA on SSCA practices within companies?* To be able to answer this question, it is essential to gather the perceptions and beliefs with our questionnaire of several SC professionals from different country and industry areas on the factors that influence their companies for selecting a certain sustainability strategy. Some factors related to sustainability implementation at companies have some historical events which are very important to know about them in order to provide justification for the companies' behavior toward sustainability. The second research question is related to *How the use of certain tools and techniques of BDPA impacts the effectiveness of decision-making on sustainable supply chain analytics performances?* This requires conducting the study at several levels such as within companies by considering the current data that they use to calculate their performances over sustainability to obtain effectiveness on decision-making. Therefore, studying sustainability in its natural settings can be achieved through case studies. As indicated by (Dubois & Gadde 2002), the interaction between the phenomenon and its context is best understood through in-depth case studies. *The third research question focuses on how do internal practices compete with external pressure in the adoption of BDPA for SSCA policies and practices?* Gathering the views and perceptions of "THE COMPANY A" and their employees is essential in order to understand the impact of the internal and external factors/enablers of BDPA on sustainability implementation and spread on the supply chain. For example, internal and external pressures of BDPA are tricky subjects and companies may not admit that these factors can affect them to engage in sustainable SCA. Therefore, a case study is more appropriate to capture actors' perceptions of the impact of BDPA on sustainability spread in supply chain analytics.

5.2 Company Background

"THE COMPANY A" started operations on April 16, 1995, in the Atlantic entrance of the Republic of Panama, it is adjacent to the Colon Free Zone (CFZ) location. The project area, known as South Coco Solo, was a naval airbase from the United States during World War II which it reverted subsequently to Panama due to the Torrijos-Carter treaties of 1977. In Figure 24, you will see an aerial view of the company under study.

Figure 24: Facilities. Source: "THE COMPANY A"

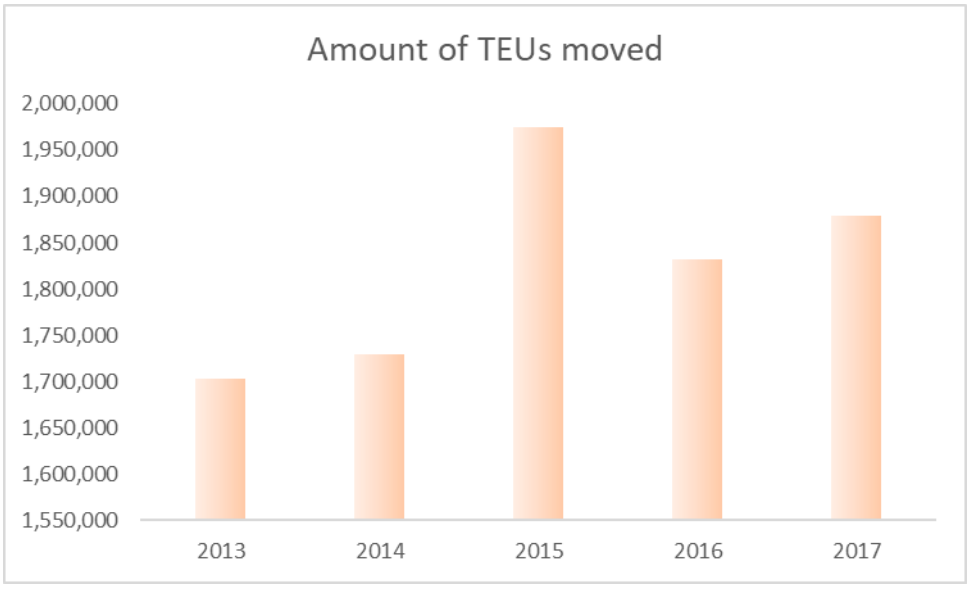
After the reversion of the lands to the Republic of Panama, the area was used as a storage and distribution center for Latin America vehicles. In the following years, it was decided to build a pier Ro-Ro (roll-on / roll-off) to facilitate the activities of importing and re-exporting of cars from the stockyard.

In August 1993 with the arrival of multinational companies to Panama, the original concept of spring Ro-Ro became the terminal container transshipment that it is today with more than 1,600 meters quayside gantry cranes equipped with modern computer and management systems. The total cost of the project in our days has a total of more than 650 million American Dollars.

"THE COMPANY A" is part of the logistics system in the cargo movement throughout the world, as it is one of the most important port terminals in the Latin American Region. In

Figure 25 you will see the amount of twenty-foot equivalent unit (TEUs) moved by “THE COMPANY A” from 2013 to 2017.

Figure 25: Amount of Twenty-foot Equivalent Unit (TEUs) moved by the “THE COMPANY A” 2013-2017. Source: “THE COMPANY A” Statistics.



Because they can connect around 125 countries through their transshipment operations, “THE COMPANY A” statistics not only show local figures, but they are also a reflection of the global cargo movement in recent years.

In “THE COMPANY A”, they offer services for the handling of all types of containers, either for:

· Import

· Export

· Transshipment

· Re-export

Each of these operations carried out through an infrastructure that offers facilities in access areas, storage areas, among others.

5.3 Objectives

The main objective of this research is to explore the enablers of the adoption of big data that impacts on sustainable supply chain analytics within a company, which has not been investigated in depth.

This research thesis attempts to investigate the questions:

1. How the use of certain tools and techniques of BDPA impacts the effectiveness of decision-making on sustainable supply chain analytics?
2. What are the influence degrees of certain enablers that impact the effective implementation of BDPA on SSCA practices within companies?
3. How do internal practices compete with external pressure in the adoption of BDPA for SSCA policies and practices?

This research, therefore, sets out the following objectives:

To explore the role of Big Data and Predictive Analytics in a real case scenario and at the same time analyze if with the use of a simulator is possible to obtain a reduction in sustainable supply chain performances.

The problem will be addressed using a modeling technique such as predictive analytics with the development of a predictive simulator (an app for simulating certain environmental and other conditions for training purposes or experimentation.)

The objective of the study in detail is to measure the effectiveness of the adoption of BDPA on the reduction of sustainable supply chain performances (the ability of the company to include the model in their processes.)

5.4 Processes in place and Dataset

5.4.1 Processes

Considering the previous mentioned objectives, I made multiple Skype calls with the employees of “THE COMPANY A” and finally, they decided that the purchasing department was a suitable candidate for the case study because of the quantity of data (5 years of datasets), the problems that they were facing, and the controls that they want to implement. I asked to “THE COMPANY A” as much information as possible related to the purchasing processes under investigation; this is a mandatory preliminary step for following data analysis. To this extent, “THE COMPANY A” sent the flowcharts describing the current processes of their operation that you’ll see in the Annex c.

However, even though they have a standardize process flowchart and after doing interviews with the collaborators from the operation and supply chain department, the respondents affirm that the processes are empirical and most of the employees do not follow the standard process.

5.4.2 Datasets

The data file, that "THE COMPANY A" provided, will constitute the structured dataset for the analysis. Currently, "THE COMPANY A" uses Maximo from IBM as Enterprise Asset Management (EAM) software. Based on the exchanges that I had with "THE COMPANY A" and the online documentation, the view, and understanding of the data can be summarized as such as the following points[1]:

- Data was organized into two main parts: *received items* - related to the items arriving at the warehouse - and *material issues* – items removed from the inventory. In this last group, we can distinguish items removed for internal *consumption*, or *transferred* items to other locations. In this report, we focus only on consumption and reception, as we are interested in the objectives described in the previous section.
- Data were organized into commodity groups, e.g., *Maintenance, Reparation;* and each item – referenced with an *item Number* and a *description* –is associated with one of them. Moreover, each item inbound (shipped to the warehouse) was associated with an order number, a date for the order, a person in charge, a quantity and a price. Similarly, for each outbound item (taken from the inventory) we can find a quantity and a date. Each inventory movement was also associated with a person responsible for the operation, and an order number, plus some more information to relate the movement with others Maximo's operations; these details, however, are not useful now for our analysis and won't be mentioned further.

Three main batches of Maximo export have been received[2]. This data is related to the orders and internal demand for different products. Extracted datasets are in the form of structured data in the common CSV file format; these files have been transferred between the parties through a well-known enterprise secure cloud to ensure confidentiality. The first one was an initial export to validate the methodology and to understand the data structure. However, the quantity and the type of data were not satisfying for any useful analysis (a few months of data related to cafeteria commodity group). The second batch was a broader export with a longer period; this batch was used to start a data visualization approach to check the quantity a long time for each item in the inventory. The last batch was a much more complete export related to the last five years of operations and was considering all the important commodity groups, specifically related to the mechanical department. While this step by step approach took a little more time compared to a single batch exchange, it was very useful to validate the methodology, focus on the current operations processes – less data, less cleaning, only a few processes at a time - and chose the right tools. In the following report, carried analysis refers only to this complete last batch.

5.5 Methodology

[1] Here I refer only to the information that is necessary for our analysis, leaving all the unneeded details.

[2] A Non-Disclosure Agreement (NDA) was properly prepared, agreed and signed from both parties before.

Data analysis was conducted in two steps: a qualitative approach aimed at understanding the non-measurable big picture of the situation and a quantitative approach to measure the metrics of interest. For both, the data has been manually analyzed through dedicated software in Python - that was developed for this task – and the well-known Elastic Search software for a standard big data approach. For the sake of comparison, I tried to use - with smaller data exports - Excel Spreadsheets as done by “THE COMPANY A”; this tool is however not appropriate for larger data quantities and becomes quickly un-exploitable if customized analyses are needed.

The analysis has been conducted along approximately 8 weeks at the end of 2017 and at the beginning of 2018.

5.5.1 Qualitative Approach

The qualitative approach is straightforward. As said, I have been able to reconstruct the evolution of the quantity of each item along the five years of the dataset. The evolution was then plotted and checked visually. An example is provided in Figure 26. A similar approach has been used for checking the quantity of material ordered per single order. This last operation was done only for a random subsample of the dataset in order to test the methodology on a smaller subset. Additionally, there is no need to plot the entire dataset to validate the method.

Figure 26: an example of quantity evolution for one item in the dataset. Flat parts of the graph correspond to periods in which there is no evolution based on the data received.

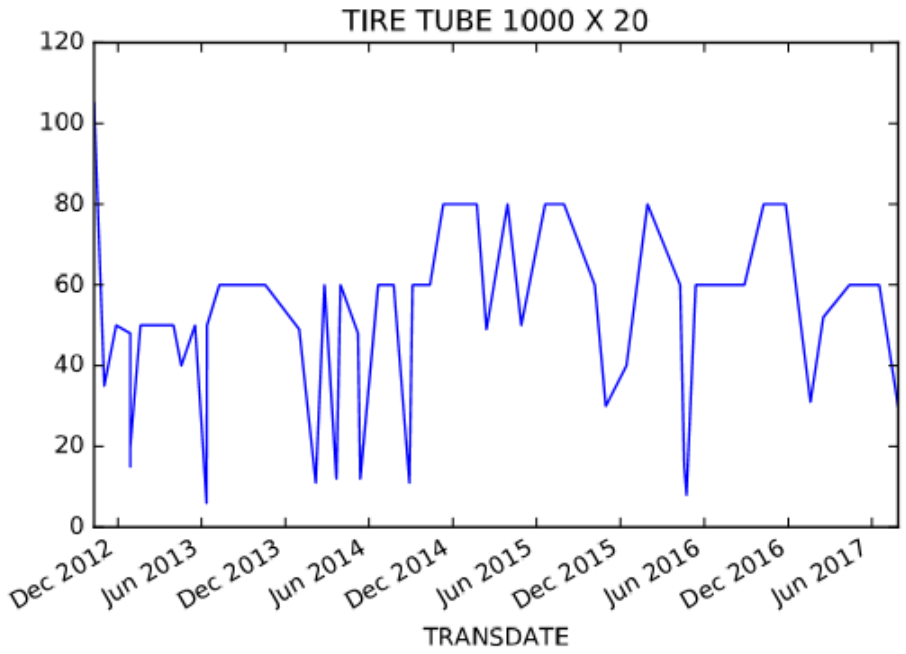
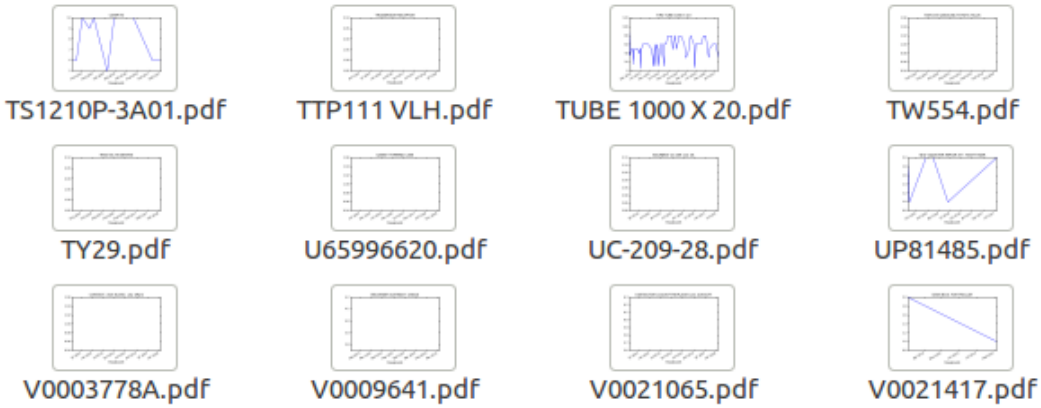


Figure 27: An extract of the evolution of the order for each item, focusing on items with a low number of samples.

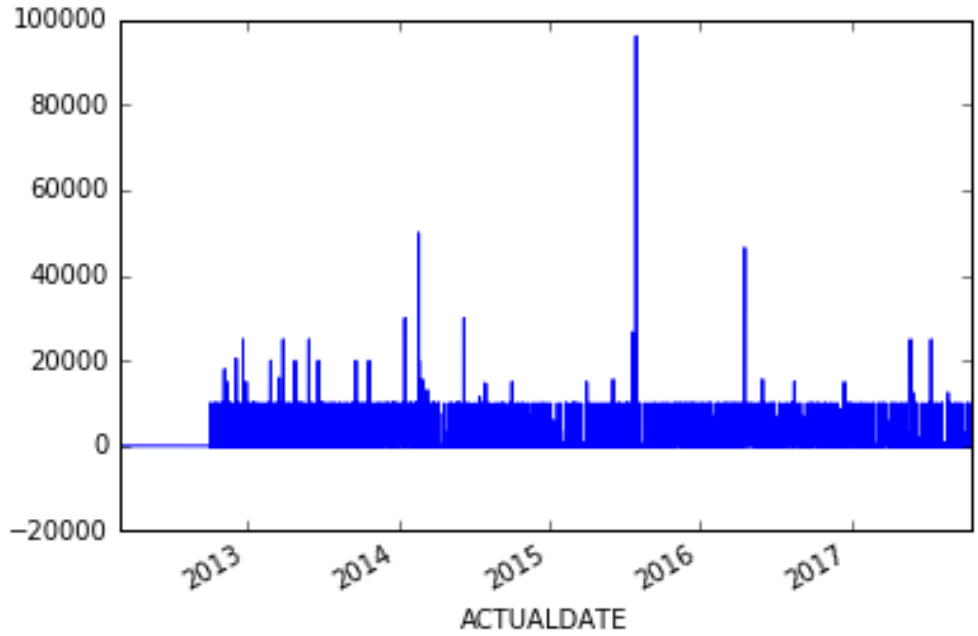


It appeared immediately from the qualitative analysis that for some items there is an insufficient number of orders to measure the evolution reliably. For example, in Figure 27, some graphs present no evolution at all (meaning that there is only one sample, e.g., the current quantity) or few sharp connected lines (meaning that few samples are present and with a significant delay between them.) Besides, the smaller the number of orders, the lower the reliability of an estimate is made in subsequent calculations (e.g., calculation of lead-times).

Qualitative analysis also had shown an uneven pattern in ordered quantity, as shown in the example in Figure 27. A more detailed inspection of these patterns revealed that for **some items the ordered quantity has outlier values or even errors**. In the example of Figure 28, I found "6000024018" in the ordered quantity: this was indeed the item number[3]. While the need for dealing with outliers is a well-known problem in statistics (e.g., quantile analysis); the errors will have a strong negative impact on many KPIs that will be suggested after our analysis.

[3] In shown figure, the error due to item numbers has been already removed in order to be able to visualize the data

Figure 28: plot of quantity of material ordered for each order of one item.



Quantitative analysis using big data analysis approach was used on the following points:

I. To remove the visible errors.

II. To plan an error recovery strategy for the quantitative analysis (where possible).

5.5.2 Quantitative Approach

ABC analysis: The challenge here was the analysis of more than 10000 items, so this analysis was used to focus efforts on the important ones.

To make the ABC, it was counted the number of occurrences per item that is to say how many orders have been issued for that item. It is important to notice that for this purpose was relied on the item number indicated in the dataset. You can see these results in the histogram indicating the most items ordered.

This analysis highlighted a very important point because **it has been found many empty item numbers**[4]as you'll see in Figure 29 and Figure 31. To be more specific 21% of item numbers were empty, and for this reason, the quality of the analysis will not be 100% accurate due to the quality of the data.

[4]In few cases item number references were wrong (e.g. format errors); we are not going to detail here all the different errors, as it does not add any more value to the main point.

Figure 29: products with empty Item Numbers

DESCRIPTION	ITEMNUM
Sodas malta vigor	10002804
Sodas pepsi cola Cj.	10002802
Sodas squirt Cj.	10002804
Sodas ginger ale Cj.	10002804
Sodas 7up Cj	10002804
Sodas orange crush Cj.	10002804
JUGO DE PIÑA KERNS cj/24und	nan
JUGOS DE MANZANA KERNS cj24unds	nan
JUGOS SURTIDOS	nan
JUGO DE MELOCOTON KERNS cj/24unds	nan
JUGO DE PERA KERNS cj/24unds	nan
AQUA CRISTALINA 5GAL.	10005280
CAFE Lb. 20lbs.xblto.	10002744
Azucar En sobres 5 Cj X PK/250sobres	10002737
Te, caja de 24 cartones de 100 bolsitas	10002791
Revolvedor de Café cj/1000unds	10002787
Azucar 1 Lb.XPK. 25lbs.xblto.	10002738
Clorox, 6 X 0.5 Gal	10016608

Twelve (12) items were separated with the greatest value as items in the group A. This choice is empirical and based on the histogram found as you will see in Figure 31; however, this choice should be later reconsidered by operators within the normal operations and especially after the data cleaning. 6% of the items represent 80% of the total net consumption of the maintenance department. These items sum more than 10 million dollars, approximately 52% of the net consumption of the maintenance department. However, the assets that represent the 21% I don't know which asset or family belongs to because the cells were empty again (quality of data was missing) as you will see in Figure 29.

Figure 30: ABC Graph. Source: Author

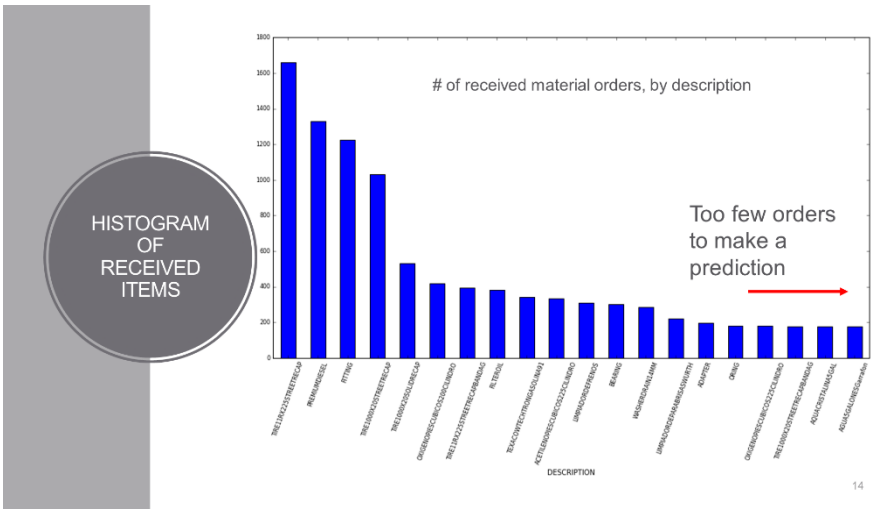
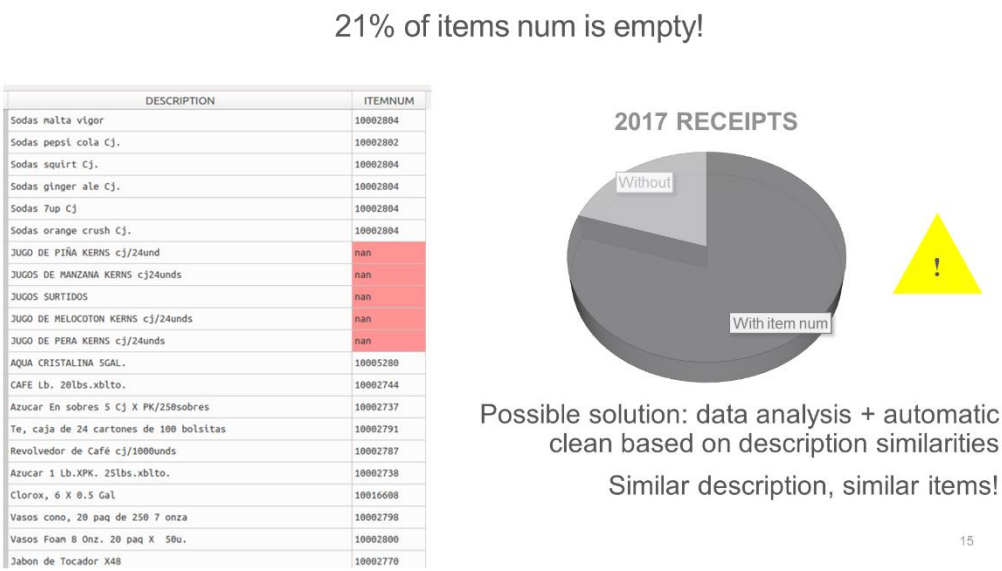


Figure 31: 21% of items numbers were empty



Many items have multiple sub-items as you can see in Figure 32 below. It is important to make this type of analysis because it is easy to understand the real picture from the data. For example, understand the behavior of the item group by families, or understand how much space is taken by "tires" (by macro category). The problem is that the item numbers are different per product and do not reveal this picture. And for this reason, I should work with the product description. The problem is that (while systems to search in the text are available) the text is mixed with Spanish and English as you will see in Figure 32 (e.g., the same item with two descriptions "toner Amarillo," and other "Yellow toner".)

Figure 32: Detail of order histogram for one specific item with multiple sub-items (categories)

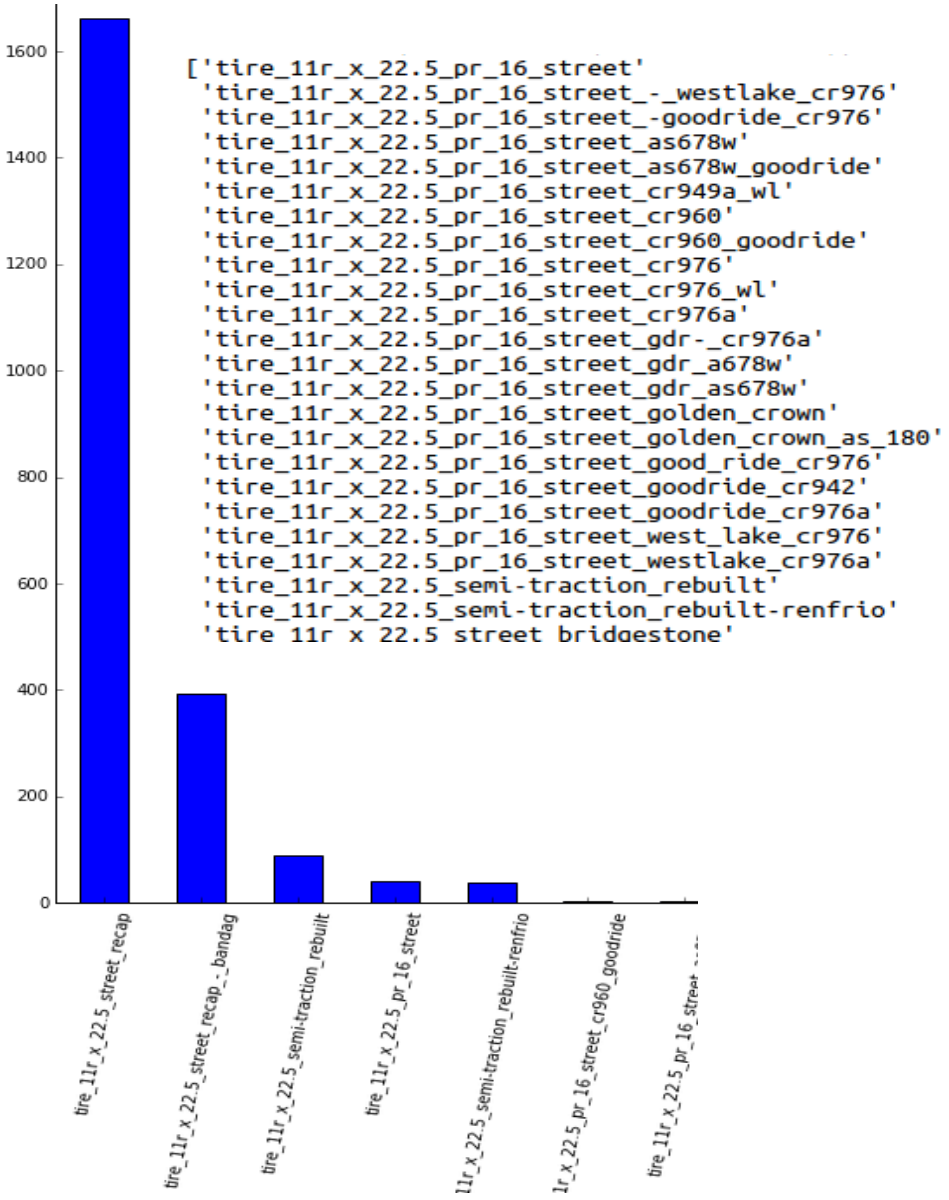
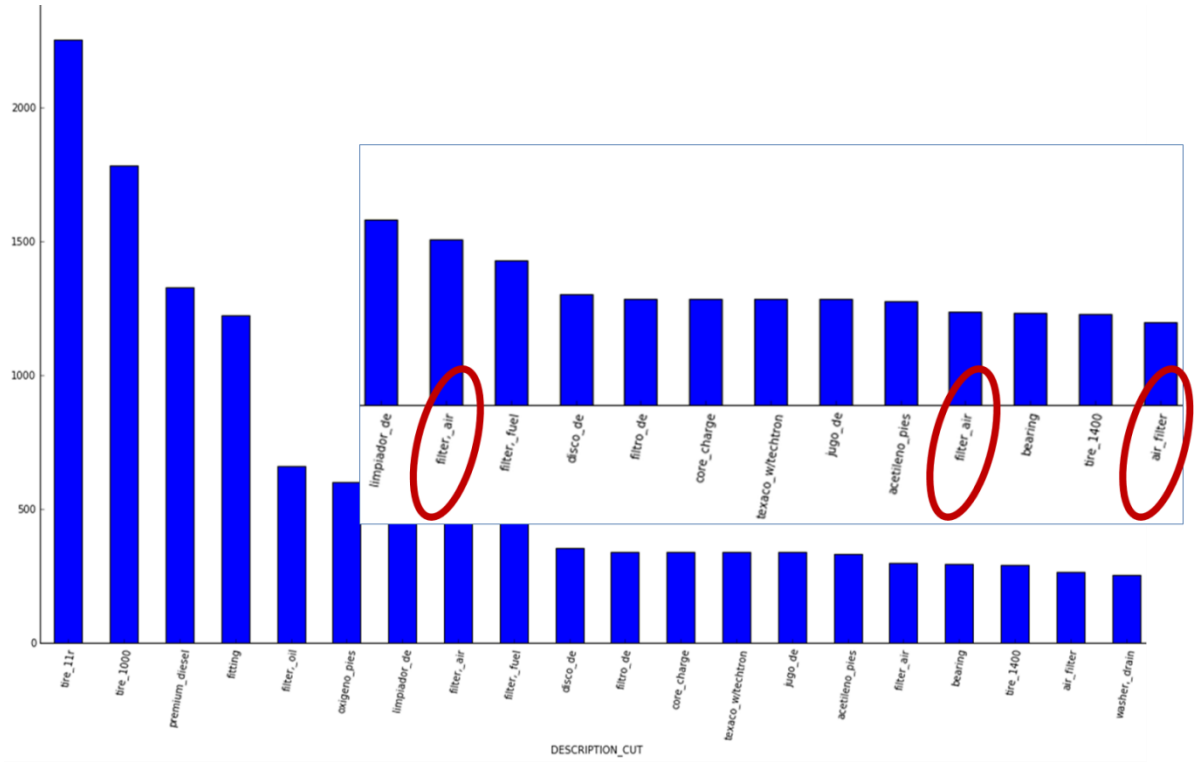


Figure 33: Data visualization can help. Beware of names vs. item number



Inventory Turnover Ratio (ITR): it is one of the efficiency ratios and measures the number of times on average. The inventory is sold and replaced during the fiscal year. **Inventory Turnover Ratio formula that we used for this case study was:**

$$ITR = \frac{COGS\ (Costs\ of\ Goods\ Sold)}{Average\ Inventory}$$

$$COGS = Beginning\ Inventory + Purchasing - Ending\ Inventory$$

$$= \frac{Average\ Inventory}{\frac{Beginning\ Inventory\ Balance + Ending\ Inventory\ Balance}{2}}$$

Inventory Turnover Ratio (ITR) is an indicator to measure how a company can control its merchandise efficiently. This analysis shows the company that the purchasing department does not overspend by buying too much inventory and waste resources by

storing non-moving inventory. It also shows that the company is capable of selling, moving or transferring effectively the inventory it purchases.

It also shows the liquidity of the inventory. Inventory Turnover Ratio is figured as ***"turnover times."*** Average inventory should be used for the inventory level to minimize the effect of seasonality.

The (ITR) was calculated from the 60 most important items that were obtained from the ABC analysis. In this case study, it shows some of them to be precise and concise. As you can see in Figure 34, some of the ITR values are negative. This situation was analyzed more in detail, and it can be inferred that the negative values are because they did not store the current balance until September 2016.

Figure 34: Inventory Turnover Ratio (ITR)

desc	itr
CHEVRON URSA PREMIUM TDX 15W40 (55/208)	0.937
AGUA 5 GALONES. (Garrafon)	36.5
FILTER, HYDRAULIC OTTAWA HF6510, BT839, LFP1652, LFH4209, P551553, 51196	7.21
PLUG FOR 480 V FOR WELDING MACHINE	3.55
FILTER, OIL S/P(P558615), BT339, LF-3806, LFP780, 51507MP	4.27
FREON TANK 134A 30 LBS	0.919
CONTACT CLEANER 500ml	-0.898
SUNBRITE (AIR CONDITIONING CLEANER)	7.27
BRAKE CLEANER 500 ml	4.47
SPLICE KIT (box of 25 pcs)	3.4
CHEVRON 1000 THF (55/208 DR)	0.458
FILTER DIESEL FP585F, BF988, FP586F, LF3521, FF42000, 33358	6.74
FILTER, FUEL BF1352-SPS	8.07
HAVOLINE SAE 10W30	2.21

Figure 35: Quantity evolution for one item in the dataset. As we can see, the current balance was not updated correctly in some cases.

Index	ITEMNUM	CURBAL	QUANTITY	UNITCOST
2016-01-29 14:16:00	893-961	0	-200	5.6
2016-03-01 12:32:00	893-961	0	-250	5.6
2016-04-18 16:24:00	893-961	0	-200	5.6
2016-05-13 11:13:00	893-961	0	-200	5.6
2016-06-16 09:57:00	893-961	0	-200	5.6
2016-07-16 13:54:00	893-961	0	-200	5.6
2016-08-11 13:41:00	893-961	0	-250	5.6
2016-09-05 20:26:38	893-961	3.78e+03	-1	5.64
2016-09-06 02:10:47	893-961	3.78e+03	-1	5.64
2016-09-06 07:31:01	893-961	3.78e+03	-1	5.64
2016-09-06 12:03:00	893-961	3.78e+03	-2	5.64
2016-09-06 12:03:38	893-961	3.78e+03	1	5.64
2016-09-06 17:12:57	893-961	3.78e+03	-1	5.64
2016-09-06 17:18:57	893-961	3.78e+03	-1	5.64

- As you can see in Figure 35, some of the calculated items had a relatively low ITR in comparison with the rest of the items on the list, except the "*agua 5 galones*". You will wonder, what is the optimal inventory turnover ratio? Well, the maximum ITR is restricted by factors such as replenishment frequency. There are two possible reasons for a low ITR:

    - **Low quality of the inventory management software system or**
    - **Powerful inventory management software system such as Maximo, but a shortfall of proper setup by users or/and user training.**

  An optimal ITR is no absolute value because it is a very individual indicator for every single company. The average ITR from the same industry group is not a measure to follow either. Even the best ITR in your industry can be improved by **making the right decisions based on reliable data.**

  How to interpret the ITR Analysis?

  Example :

FILTER, OIL S/P(P558615), BT339, LF-3806, LFP780, 51507MP	4.27

“THE COMPANY A” converted the total of its inventories of Filter; oil S/P… into cash or account receivable 4.27 times that year.

a. **A low inventory turnover ratio** is a signal of inefficiency since inventory usually has a rate of zero return. It also implies either poor sales or transfers to other departments or excess inventory. A low turnover rate can indicate poor liquidity, possible overstocking, and obsolescence, but it may also reflect a planned inventory buildup in the case of material shortages or anticipation of rapidly rising prices.
b. **A high inventory turnover ratio** implies either strong sales or ineffective purchase (the company buys too often in small quantities; therefore, the purchase price is higher.) A high inventory turnover ratio can indicate better liquidity, but it can also indicate a shortage or inadequate inventory levels which may lead to a loss in business. High inventory levels are usually unhealthy because they represent an investment with a rate of zero return.

Days of Inventory on Hand Ratio (DOH): The direct cost attributable to the production or purchasing of the goods sold or trespasses to another department by a company during its fiscal year. **Days of Inventory on Hand (DOH) :**

$$\frac{365 \; or \; 360 \; days \; depending \; of \; the \; company}{ITR}$$

The (DOH) was calculated with the 60 most important items that were obtained from the ABC analysis. In this case study, it just shows some of them to be precise and concise. As you can see in Figure 36 below, some of the DOH values are negative or with very high values. As mentioned before, the negative values are due to the absence of information on the current balance until September 2016.

Figure 36: Calculation of ITR and DOH in Python and exported to Excel for a better presentation.

Descripción	Rotación de Inventario	dias de inventario
CHEVRON URSA PREMIUM TDX 15W40 (55/208)	0,94	389,468
AGUA 5 GALONES, (Garrafon)	36,51	9,999
FILTER; HYDRAULIC OTTAWA HF6510; BT839; LFP1652; LFH4209; P551553; 51196	7,21	50,609
PLUG FOR 480 V FOR WELDING MACHINE	3,55	102,774
FILTER; OIL S/P(P558615); BT339; LF-3806; LFP780; 51507MP	4,27	85,471
FREON TANK 134A 30 LBS	0,92	397,315
CONTACT CLEANER 500ml	-0,90	-406,436
SUNBRITE (AIR CONDITIONING CLEANER)	7,27	50,235
BRAKE CLEANER 500 ml	4,47	81,629
SPLICE KIT (box of 25 pcs)	3,40	107,294
CHEVRON 1000 THF (55/208 DR)	0,46	796,127
FILTER DIESEL FP585F; BF988; FP586F; LF3521; FF42000; 33358	6,74	54,188
FILTER; FUEL BF1352-SPS	8,07	45,252
HAVOLINE SAE 10W30	2,21	165,506
FITTING; AIR LINE B/C - KF035	3,80	96,092
PENETRANTE ROST OFF 300ml	-0,98	-374,276
DRIVE AXLE OIL	1,39	262,739
FILTER	6,14	59,443
FILTER AIR AH1197; P537454	8,18	44,648
FILTER; COOLANT BW5075 (P552075)	7,57	48,225
TIRE TUBE 1000 X 20	5,59	65,263
FREQUENCY CONVERTER DUAL COMPARTMENT REPLACES 818242C	10,90	33,480
CHAMBER; AIR KFR-174	10,81	33,760

How to interpret the DOH Analysis?

Taking the same item that we used in the previous example:

FILTER; OIL S/P(P558615); BT339; LF-3806; LFP780; 51507MP	4,27	85,471

We can see that “THE COMPANY A” in order to meet the demand for this product, they need to store it for **85,471 days**. We can conclude that an increase in the number of days of storage can be harmful to the company since it implies to assume more costs.

The ITR and DOH are inversely related. If inventory turnover is high, the DOH will be low and vice versa. Days in Inventory results should only be compared to industry averages and with the company's prior ratio since the averages vary significantly from one industry to another. It is important to compare the company's results over time and determine the trend.

If the number of days increases, the company may face a decline in sales/transferences, or it increases its inventory faster than the sale/transference growth.

If the number of days decreases, the company may face the future loss of sales/transferences due to stock-outs if the level of inventory is too low.

DOH is a critical financial measure, but in the field of supply chain, its uses are very helpful. DOH does not give a definitive answer on its own. The results should always be interpreted relating to other indicators and should be part of a future SCM performance scorecard design for purchasing and inventory areas.

Correlation Analysis or Co-occurrence of orders:

Correlation analysis is a method of statistical evaluation used to study the strength of a relationship between two: numerically measured and continuous variables. This analysis is useful when we want to establish if there are possible connections between variables. It is often misunderstood that correlation analysis determines cause and effect; nevertheless, this is not the case because other variables that are not present in the research may have impacted on the results.

If the correlation is found between two variables it means that when there is a systematic change in one variable, there is also a systematic change in the other; the variables vary together over a certain period. If there is a correlation found, depending upon the numerical values measured, this can be either positive or negative.

If there is a correlation between two numerical sets of data, positive or negative, the coefficient worked out can allow you to **predict future trends** between the two variables. Still, you must remember that you cannot be 100% sure that your prediction will be correct because correlation does not determine cause or effect.

In the case of “THE COMPANY A”, it was used exploratory analysis to consider for modeling the order process and make predictions are the correlation among different orders. The idea is simple:

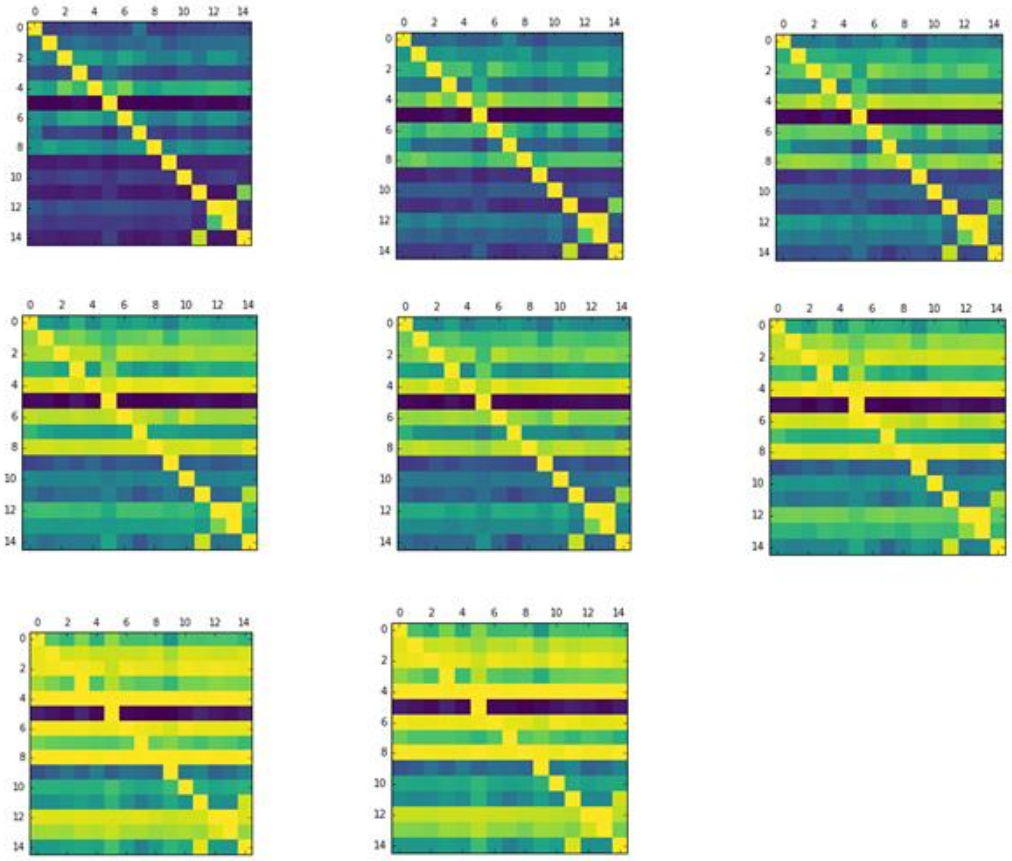
To make an example, suppose that Tires type “A” is very often ordered together with Tires type “B”; the next time an order contains Tires “A,” It can be checked automatically if Tires “B” are in stock or suggest ordering them. Of course, the analysis can be taken a step further considering the quantity of ordered material. In addition, the distance in a time of the orders; in fact, very often the analysis is useful when this "correlation" isn't obvious (e.g., tires “B” is often ordered after few days). In these cases, making good predictions can save time and money (e.g., placing one order instead of two).

For this analysis, it was considered the order data from “THE COMPANY A”. For each order, it has been checked which item was ordered in another separate order emitted in the “N” following days; this is the *time delta* to compute and plot the co-occurrences. It can be repeated the analysis considering different deltas. However, “THE COMPANY A” has more than 10000 different items in inventory. For time and resource limitations, this study focused on the first 15 items coming from the ABC analysis. Moreover, in this first analysis, the order quantity was not considered.

Results show that some small co-occurrences appear up to a time delta of a few days. Over that horizon, the orders are frequently emitted, and all the items are correlated. The analysis suggests that a deeper analysis could be carried out to get a better understanding of the process. Furthermore, considering the prices and economic costs

of orders is suggested to evaluate the savings. Results are plotted in Figures 37 in where each cell of the matrix indicates the number of times (in percentage) of the two items that were ordered together or close in time along with the dataset.

Figure 37: co-occurrence matrices for the first N items coming from the ABC.



In Figure 37, the different matrices refer to different time deltas (from 1 to 8 days). The importance of correlation is color-coded, from deep blue (low) and yellow (high). Few correlations start to appear, considering a small-time delta.

Obsolescence analysis: obsolescence is a tricky subject. Usually, obsolete inventory is a term that refers to inventory that is at the end of its **product lifecycle** and has not seen any sales or usage for a certain period, usually determined by the company. Managers should be particularly careful about obsolescence because it can cause large losses for the company. Large amounts of obsolete inventory are a warning sign for stakeholders:

c. They can be symptomatic of poor products
d. Poor demand forecast management

e. Poor inventory management

Looking at the amount of obsolete inventory that a company creates, it will give to the stakeholder an idea of how well the product is sold/used/transferred and of how effective the company's inventory process is.

However, in the case study of "THE COMPANY A", at the best of my knowledge and considering the non-perishable items[5], **the material has no expiration date[6]**. The obsolescence is also seen under the light of waste reduction: obsolete items are those that must be disposed of as unusable. While the "THE COMPANY A" data **reports some waste of material**, this quantity is **really small** and related to very few items. An analysis of this aspect will not underline anything really useful that the company does not know already.

Obsolete items, however, are not only those perished or wasted but also those that are unusable because the prior needs for this item were no longer needed (consider the case of, e.g., specific tires for a truck that is no longer in service). This point embraces the needs of the company related to the **waste of space** in the inventory.

To scope out, some items may also be wasting space regarding 'likelihood of use': the lower the likelihood to use a particular item, the lower the need of stock for such items, the higher the savings regarding space in the inventory. This last point, however, requires much more detail regarding the probability of use of one item, especially for items with *rare utilizations* but high impact. For example, this is the case of special gear to repair a fundamental crane in operations; this material will be likely to 'sit' unused in the inventory for a long time wasting space. Particular attention should be put considering this item 'obsolete': in fact, the lack of such item may be a big problem for the production if the crane fails. To be able to free the inventory from these items it requires a very precise and effective predictive maintenance analysis to be sure that such item is not required for a certain period (e.g., in the six months to come). Moreover, this period should consider the lead time required for such an item to arrive after the order, in case of need. As a final consideration, the opportunity created by such precision (the savings regarding space) must overcome the price of the risk of failure (e.g., wrong prediction -> lack of item -> loss of earnings due to production failure.) To achieve such precision, a larger amount of data and many more details regarding the modeling are needed. It should be pointed out that this is a case study and there is no time for all the calculations_ more details needed, field surveys required, deep opinions gathering from specialized personnel, data cleaning, etc.

For this reason, a good tool to help this research is to calculate the inventory percentage analysis that would be a formula that underlines which elements should be checked in priority. Moreover, this formula is complicated and that is why you should

[5] While "THE COMPANY A" data contains perishable items such as food and beverages, these do not represent the core business of "THE COMPANY A" and are not considered here.

[6] What is the definition of obsolescence for "THE COMPANY A"? When an Item for "THE COMPANY A" is obsolete?

consider for future research a machine learning approach to address this problem.

5.6 Case study conclusions

The findings from the case study enabled to identify the factors that adopted for the use of Big Data across its sustainable supply chain analytics and the impact of their implementation within a company. Based on the findings and analysis, a brief conclusion can be made to this case study in relation to the research questions.

What are the influence degrees of certain enablers that impact the effective implementation of BDPA on SSCA practices within companies?

- This case study allows you to understand a better insight of the factors that can affect the adoption of big data on sustainable supply chain analytics such as **lack of proper training skills, lack of strong policies of use, etc.** Even though, the case study by itself was not capable to get the influence degrees of certain enablers. On the other hand, the questionnaire in chapter 4 was capable to find the coefficient 0.4 which was the relationship between the questions and the factors obtained depending on the variable loadings that impact the adoption of BDPA for SSCA.

How the use of certain tools and techniques of BDPA impact the effectiveness of decision-making on sustainable supply chain analytics performances?

- Based on the discussions with the interviewees, the current tools that they are using by themselves cannot analyze data. The company needs more appropriate tools for the data analysis that should be compatible with their current software. MS Excel is a much-loved application, but it does not seem to be the appropriate application for the analysis of large datasets. At this point, Excel would appear to be of little help with big data analysis, and the process time of analysis will be longer, tedious, complicated, time-consuming, unstable, error-prone that will increase the workload of the employees.

How do internal practices compete with external pressure in the adoption of BDPA for SSCA policies and practices?

- Even though, they are using a powerful Enterprise Asset Management (EAM). It seems that they still struggle to gain value since it may be due to the contentment with the current version of the system, **lack of proper training skills**, or **worries over cost and selecting features of the current software**. According to the research that it has been done on the software, it can be affirmed that the software can make some of the tasks of advanced analytics tools and data visualizations. But these can be costly and may not allow flexibility. Moreover, this preliminary analysis aims at understanding what the top management can do with the data before a big data approach.

- Data errors prevent an accurate analysis and measuring of SSCA performances. Before any big data approach, **the company** should work in putting in place **strong policies** to **prevent errors**. If there is interest in exploiting current data, different approaches can be considered: first, empty item numbers should be addressed. A part of them can be recovered manually (operators can know the references) or by associating the item number with recurrent descriptions in the data (e.g., the same items could share the same description.) Secondly, data errors due to human mistake (e.g., the item number in the item quantity) are hard to recover but less hard to prevent; tool controls and methods can be implemented to prevent an insertion in the database (e.g., display an error message when an operator insert an outlier value in a field, asking to confirm this abnormal number.) However, software compatibility can be an issue for this task.

Chapter Six: Conclusions

6.1 Introduction

This chapter provides a summary of the main findings of the thesis, its contributions, and its limitations. The overall aim of the thesis identified research gaps and research questions that are revisited. The conclusion is drawn in ***A qualitative analysis to investigate the enablers of big data analytics that impact sustainable supply chain analytics.*** The chapter includes some methodological implications and the limitations of the thesis. Avenues for future research are discussed and the chapter and the thesis ends by a final conclusion.

6.2 Main Contributions of the Thesis

- Propose a methodology to identify the enablers of SSCA, and the necessary tools and techniques of BDPA.
- A questionnaire was written and sent it to professionals in the supply chain.
- To understand a better insight into the adoption of big data and predictive analytics.
- Identify the factors that affect the proper implementation of big data.
- Identify the coefficient relation between the questions and the factor.
- First analysis of the answers enablers to identify interest in the concepts from the respondents, but also a lack of education and training in these domains was found.

6.3 Methodological Implications

Investigating the enablers of big data that impact sustainable supply chain analytics applications and performances is challenging and the research questions formulated in this thesis require appropriate research strategy. The thesis adopted moderate constructionism (Järvensivu and Törnroos, 2010) since understanding how the enablers of big data impact sustainable supply chain analytics applications and performances. The thesis also adopted a questionnaire and a case study as a research strategy (Dubois and Gadde, 2002; Eisenhardt, 1989; Meredith, 1998) in order to capture the different perceptions of the people and companies on big data application on sustainable supply chain. The following methodological implications can be drawn:

- The importance of gathering the views of both people and companies to have a better understanding of this subject. Most of the existing literature focuses on gathering, mainly, the focal company's perception, and it neglected the views of the people or the employees on sustainable supply chain implementation using big data analytics.
- Understanding the impact of the enablers of big data on sustainable supply chain analytics requires gathering the views of companies and SC professionals. This was

useful in capturing similar and different points of view between companies and SC professionals, accordingly, contributed to a better understanding of how these enablers can impact the implementation of big data within the supply chain.

- The case study strategy is useful to have close interaction with the "THE COMPANY A" in order to get access to the required information. The interviewees and the dataset the company provide gave me various kinds of information which clarified how big data is using to implement sustainable supply chain practices.

- The case study strategy is useful in knowing about some chronological events that were critical for the company to adopt certain technology and sustainability strategies. The interviewees informed about some historical events that influenced their companies' decisions to adopt certain strategies.

- The thesis adopted the enablers of big data and predictive analytics on sustainable supply chain questionnaires and a case study strategy was useful in going beyond the focal "THE COMPANY A" dyadic relationships and gaining better perspectives on how big data and predictive analytics can be used in the implementation of the sustainable supply chain.

6.4 Thesis Limitation

The thesis focused on investigating how the enablers of big data and predictive analytics impact sustainable supply chain implementation and practices where this overall aim was cascaded down into three research questions. The findings of the thesis contributed to a better understanding of how big data impacts on sustainable supply chain. However, the thesis has several limitations. First, the thesis selected a company that is an example in sustainable supply chain operations and a leader in the region. Although the company represented one industry, other contexts and industries may reveal different sustainable supply chain strategies and practices.

Second, the thesis relied on conducting a single case study to reveal the sustainable supply chain strategies using disruptive technologies such as Big Data and Predictive Analytics. Although the primary and secondary sources of information in the case study provided rich information to answer the research questions, increasing the number of case studies could be useful to gain a better understanding of how big data affects various SSCA performances of the company. It may also assist in detecting more SSCA strategies and practices and providing a better understanding of how BDPA impacts SSCA. Third, the questionnaire in the thesis was confined to the company employees and external SC professionals from other areas and companies. Questioning suppliers and clients beyond the dyadic focus may reveal more insights on how BDPA impacts on SSCA.

6.5 Future Research

The thesis findings highlight some avenues for future research. The thesis focused on ***investigating the enablers of big data that impact sustainable supply chain analytics***. Extended research may look at how big data and predictive analytics are implemented within

the supply chain and spread at companies belonging to the service or public sectors. The future research may focus on revealing the applicability and limitations of the identified sustainable supply chain analytics (SSC+BDPA) strategies implementations and spread at the companies and suppliers in private and public sectors.

Another future research may consider in the questionnaires, the use of a broad quantity of respondents.

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Annexes

Annex a: Questionnaire on enablers for sustainable supply chain analytics (SSCA) implementation

Annex b: Output showing factors and loadings

Annex c: “THE COMPANY A” flowchart processes.

Annex a:

Questionnaire on enablers for sustainable supply chain analytics (SSCA) implementation

Questionnaire on enablers for sustainable supply chain analytics (SSCA) implementation

Confident data, for research purposes only.
Main contact: Lineth Rodríguez, lrodriguez2@audencia.com or lineth-arelys.rodriguez-pelliere@ec-nantes.fr

* Required

Introduction to sustainable supply chain analytics:

Big Data Analytics is the science of examining raw data to help draw conclusions about information. It is used in many industries to allow companies and organization to make better business decisions and in the sciences to verify (or disprove) existing models or theories. By the other hand, sustainability has become a necessary goal for businesses and a powerful strategy for competitive advantage. Sustainable innovations along the supply chain are increasingly important regarding firm competitiveness to respond to rapid changes in the market. In the past few years, we're hearing more and more about the use of big data analytics in the sustainable supply chain & logistics functions and for this reason emerged the term "Sustainable Supply Chain Analytics". Scholars had highlighted the need by organizations to manage and collaborate closely with suppliers and customers on sustainability issues to achieve better control of risks and organizational sustainability. They have the goal to provide the appropriate information that can be used for effective and efficient decision-making on sustainability issues, and they already identified several enablers for successful implementation of SSCA. However, there is no research completed that seeks to identify the influence degree of each factor for facilitating/delaying sustainability adoption. The aim of this questionnaire is estimate the impact factor of enablers/disruptions using big data and predictive analytics on sustainable supply chain.

'Sustainability' encompasses environmental, social and economic factors (e.g. reducing carbon emissions and waste, increasing water efficiency, diversity, and promotion of well-being, equal opportunities, creating a strong, stable, efficient and fair economy).
'Sustainable supply chain' can be defined as the process used to secure the acquisition, storage, distribution of goods and services in a way that ensures that there is the least impact on society and the environment throughout the full life cycle.

1. **Age** *

_____

2. **Gender** *
Mark only one oval.

- ◯ Male
- ◯ Female

3. **Geographical area of company's work** *
Mark only one oval.

- ◯ US / Canada
- ◯ Europe
- ◯ Latin America
- ◯ Other: _____

4. **Area/Department in the Company:** *
Mark only one oval.

- ◯ Supply Chain Management
- ◯ Logistics
- ◯ Procurement / Purchasing
- ◯ Planning
- ◯ Manufactoring
- ◯ Other: _____

5. **Role within the Area/Department** *
Mark only one oval.

- ◯ Director
- ◯ Manager
- ◯ Analyst
- ◯ Engineer
- ◯ Other: _____

6. **Please describe your role/position if the above didn't apply to you:** *

_____

7. **Years of Experience** *

Questions, part 1

8. **1. How do you assess influence of SSCA practices on organization and management, processes and logistics within the next 10 years (2018-2028)?** *
Mark only one oval.

- It is not relevant (SSCA is not strictly defined, so maybe but in distant future).
- It is average (SSCA is one of many practices that are considered nowadays).
- It is strong (SSCA is one of the promising and dynamically developing practices).
- It is critical (SSCA is one of the crucial practices that will change operation and strategy on many companies).

9. **2. As an expert advising on the issue of implementation of sustainable supply chain analytics, identify internal enablers of that decision and assess their importance.** *
Mark only one oval per row.

	Not at all	Small extent	Some extent	Moderate extent	Great extent	Don`t know
Number and size of resources owned.						
Fitness of resources owned.						
IT systems implemented (ERP, WMS, EAM, etc.)						
Automatic identification systems (GS1, RFID) and data interchange systems (EDI) implemented						
Resources layout (allocation and availability)						
Other (please specify below):						

10. **other:**

11. **Intangible Assets** *
Mark only one oval per row.

	Not at all	Small extent	Some extent	Moderate extent	Great extent	Don`t know
Competitive position						
Range of the offer						
Territorial scope of business activity						
Flexibility of operation and innovation transfer						
Organizational maturity						
Organization culture						
Efficiency at operational level						
Other (please specify below):						

12. **other:**

13. **3. What external enablers of sustainable supply chain analytic implementation do you find important?**

Questions, part 2

Please answer the questions following the scale below:

i. Not at all
ii. A small extent
iii. Some extent
iv. A moderate extent
v. A great extent
vi. Don’t know

TERMINOLOGY
Greenwash: a superficial or insincere display of concern for the environment that is shown by an organization (Collins English Dictionary)

14. **How important ...** *

Mark only one oval per row.

	Not at all	A small extent	Some extent	A moderate extent	A great extent	Don't know
...is commitment from management to achieve sustainability in supply chain analytics?						
.... is for top management to avoid greenwash?						
...are governmental regulations to achieve sustainability in supply chains analytics?						
... is for you the cost of implementing green logistics within your company?						

15. **To what extent do...**

Mark only one oval per row.

	Not at all	A small extent	Some extent	A moderate extent	A great extent	Don't know
... international agreements help achieve this cause? (CDP, ISO 14001, UNEP FI etc.)						
... information and business analytics create a competitive advantage for your organization within its industry or markets?						

16. **Do domestic and environmental policies have a major impact in companies adopting sustainable practices?**

Mark only one oval per row.

	Not at all	A small extent	Some extent	A moderate extent	A great extent	Don't know
.						

17. **If customers are aware of the benefits of sustainability, will it have an impact on your processes or products?**

Mark only one oval per row.

	Not at all	A small extent	Some extent	A moderat extent	A great extent	Don't know
.						

18. **How much impact do you think use of big data tools and techniques can in achieving sustainability?**

Mark only one oval per row.

	Not at all	A small extent	Some extent	A moderate extent	A great extent	Don't know
.						

19. **How has your access to useful data changed during the past year?**

Mark only one oval per row.

	Not at all	A small extent	Some extent	A moderate extent	A great extent	Don't know
.						

20. **How often do you feel you have the right data needed to make key business decisions?**

Mark only one oval per row.

	Not at all	A small extent	Some extent	A moderate extent	A great extent	Don't know
.						

21. **For purposes of your data-driven decisions, how is the data of your organization?** *

Check all that apply.

- [ ] Complete
- [ ] Timely
- [ ] Relevant
- [ ] Consistent
- [ ] Reliable
- [ ] Detailed
- [ ] Accessible

22. **What makes creating competitive advantage from analytics difficult for your organization? (Select all that apply)**
Check all that apply.

- [ ] We have just begun to apply analytics and need more experience
- [ ] We aren't sure how to apply the analytical insights to our business
- [ ] We haven't acted on the insight from analytics.
- [ ] We are using analytics, but so are our competitors.
- [ ] Analytics is not a priority for senior management.
- [ ] We do not use analytics to drive strategic decisions.
- [ ] Other: _____

23. **To what extent do you agree with the following statement? Analytics has helped improve my organization's ability to innovate**
Mark only one oval per row.

	Not at all	A small extent	Some extent	A moderate extent	A great extent	Don't know
.	◯	◯	◯	◯	◯	◯

24. **To what extent do the following statements describe your organization?** *
Mark only one oval per row.

	Not at all	Small extent	Some extent	Moderate extent	Great extent	Don`t know
Your organization uses customer feedback to inform decision-making.	◯	◯	◯	◯	◯	◯
Your organization uses detailed data to tailor specific offerings to individual customers.	◯	◯	◯	◯	◯	◯
Your organization's customers are engaged with your organization	◯	◯	◯	◯	◯	◯
Your organization's customer intelligence has improved since last year	◯	◯	◯	◯	◯	◯

Improvement of product characteristics and services

BDPA has been successfully used to improve products and services through the analysis of large customer feedback. For examples: 1. Netflix uses BDPA to commission original programming content that appeals globally as well as purchasing the rights to films and series boxsets that they know will perform well with certain audiences. 2. By looking at historical transactions and incorporating more than 100 variables, American Express employs sophisticated predictive models in place of traditional business intelligence-based hindsight reporting. This allows a more accurate forecast of potential churn and customer loyalty.

25. **Supposing that such utilization of BDPA is possible within your company, how likely would you implement BDPA?**

_____

_____

_____

_____

_____

26. **To what extent does adoption of green practices have an impact on:** *
Mark only one oval per row.

	Not at all	A small extent	Some extent	A moderate extent	A great extent	Don't know
How effective would lean processes and cutting of wastes be in achieving sustainable supply chain analytics?	◯	◯	◯	◯	◯	◯
Green Purchasing helps in making the supply chain more sustainable?	◯	◯	◯	◯	◯	◯

27. **Would you...**
Mark only one oval per row.

	Yes	No	Maybe
... use BDPA to turn your purchasing more green or sustainable?	◯	◯	◯
... implement BDPA if it could improve your purchasing?	◯	◯	◯
... implement BDPA if it could make your company more green?	◯	◯	◯

Open-ended suggestion and comments

Thank you for participating in this questionnaire.

28. **Would you like to comment on any of the SSCA enablers in the questionnaire above?**

29. **Are there any other enablers or relationships that you may want to suggest and rate on a scale of one (1) to five (5)?**

Click below to submit! Thank you!

If you need more information, please contact us

Lineth Rodríguez, lineth-arelys.rodriguez-pelliere@ec-nantes.fr
Catherine Da Cunha, catherine.da-cunha@ec-nantes.fr
Mihalis Giannakis, mgiannakis@audencia.com

Ecole Centrale de Nantes-Audencia Business School
1 Rue de la Noé BP 92101, 44321 Nantes
Tel. : +33 240 371 600

Online questionnaire: Filippo Mazza and Lineth Rodriguez

Annex b:

Output showing factors and loadings

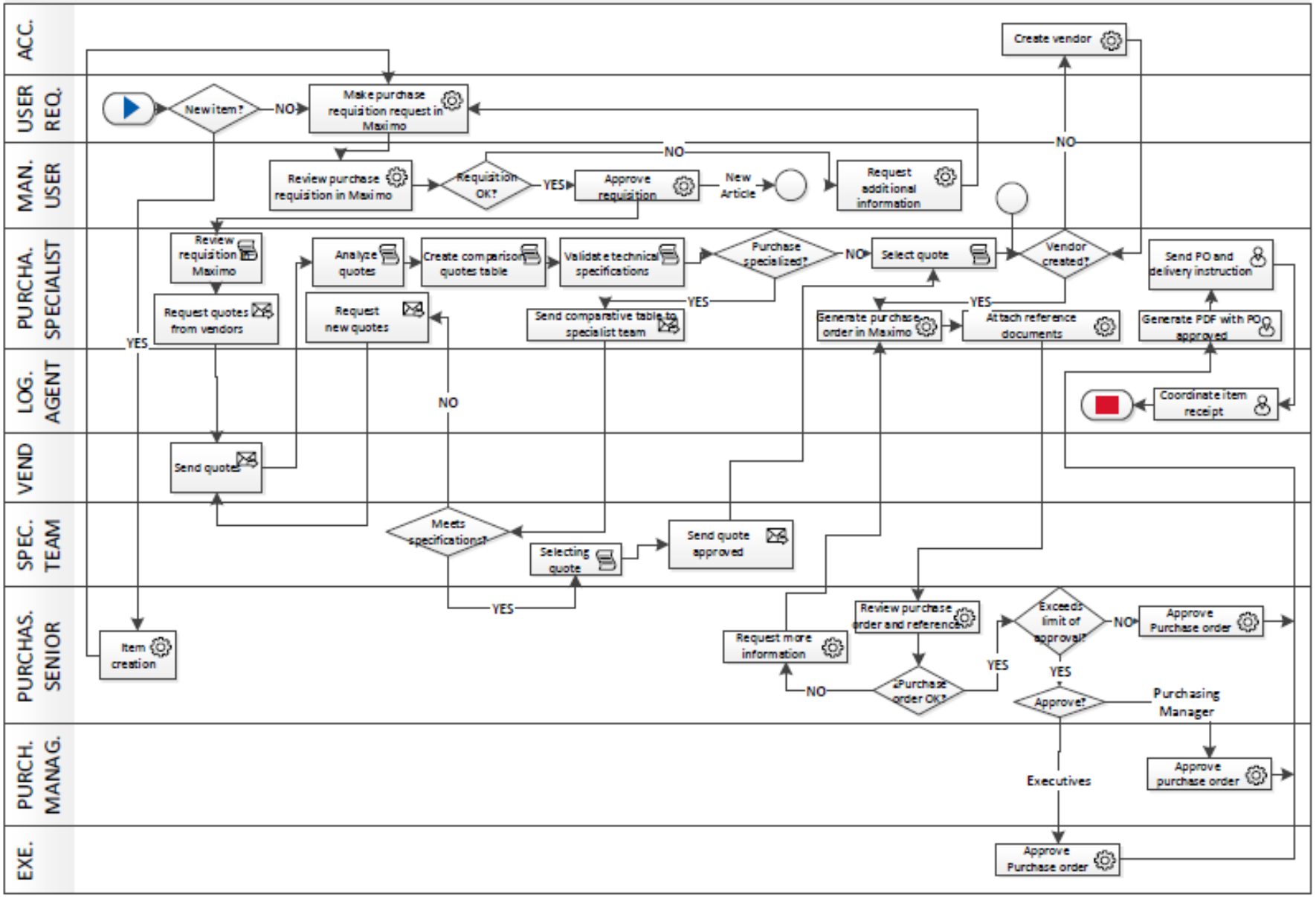
Question	C0	C1	C2	C3	C4	C5	C6	C7	C8	C9	C0_	C1_	C2_	C3_	C4_	C5_	C6_	C7_	C8_	C9_
	0.4										Internal	IT	Business size	Wish	External	Experience	Customer engagement	Management	Data Quality	More external
Age	-0.05	-0.09	-0.02	0.05	0.09	0.79	#	0.11	0.01	-0.10	-	-	-	-	-	0.79	-	-	-	-
Years.of.Experience	-0.15	0.15	-0.06	0.05	-0.02	0.84	#	0.03	-0.01	0.09	-	-	-	-	-	0.84	-	-	-	-
Influence.of.SSCA.within.10.years	0.63	0.07	-0.10	0.08	0.27	0.01	#	-0.26	-0.18	0.00	0.63	-	-	-	-	-	-	-	-	-
Importance.of.Number.and.size.of.resources.owned	0.73	0.03	0.01	-0.25	0.16	-0.28	#	0.06	-0.02	0.00	0.73	-	-	-	-	-	-	-	-	-
Importance.of.Fitness.of.resources.owned	0.89	-0.02	-0.08	0.04	0.05	0.01	#	0.06	-0.06	0.02	0.89	-	-	-	-	-	-	-	-	-
Importance.of.IT.systems.implemented	0.44	0.42	0.02	0.17	0.09	-0.06	#	0.00	0.11	0.03	0.44	0.42	-	-	-	-	-	-	-	-
Importance.of.Automatic.identification.systems.and.data.interchange.systems	0.25	0.51	0.00	0.35	0.14	-0.01	#	0.27	0.08	-0.08	-	0.51	-	-	-	-	-	-	-	-
Importance.of.resources.layout..allocation.and.availability.	0.43	0.39	0.36	0.29	-0.14	-0.28	#	0.20	-0.02	-0.05	0.43	-	-	-	-	-	-	-	-	-
Intangible.Assets..Competitive.position.	0.33	0.22	0.06	0.16	0.04	0.41	#	0.09	0.16	0.06	-	-	-	-	-	0.41	-	-	-	-
Intangible.Assets..Range.of.the.offer.	0.41	0.12	0.47	-0.03	0.23	-0.26	#	-0.04	0.05	-0.18	0.41	-	0.47	-	-	-	-	-	-	-
Intangible.Assets..Territorial.scope.of.business.activity.	0.23	0.14	0.60	0.06	0.19	-0.18	#	0.10	-0.06	-0.15	-	-	0.60	-	-	-	-	-	-	-
Intangible.Assets..Flexibility.of.operation.and.innovation.transfer.	0.61	0.22	0.05	0.20	0.26	0.15	#	0.03	-0.10	0.14	0.61	-	-	-	-	-	-	-	-	-
Intangible.Assets..Organizational.maturity.	0.41	0.19	0.13	0.09	0.02	0.24	#	0.09	-0.48	0.20	0.41	-	-	-	-	-	-	-	-0.48	-
Intangible.Assets..Organization.culture.	0.68	0.18	-0.01	0.21	-0.19	-0.02	#	0.13	0.00	0.12	0.68	-	-	-	-	-	-	-	-	-
Intangible.Assets..Efficiency.at.operational.level.	0.55	0.20	0.35	0.15	-0.06	0.05	#	0.16	0.05	0.19	0.55	-	-	-	-	-	-	-	-	-
Intangible.Assets..Other..please.specify.below...	0.30	-0.10	0.20	-0.25	-0.03	-0.13	#	-0.10	-0.43	0.30	-	-	-	-	-	-	-	-	-0.43	-
Importance.of.commitment.from.management.to.achieve.sustainability	0.02	-0.16	-0.10	0.06	0.20	-0.05	#	0.72	0.15	0.32	-	-	-	-	-	-	-	0.72	-	-
Importance.of.for.top.management.to.avoid.greenwash	0.22	0.05	-0.15	0.03	0.58	0.05	#	-0.03	0.02	0.08	-	-	-	-	0.58	-	-	-	-	-
Importance.of.governmental.regulations	0.11	-0.04	-0.01	-0.11	0.74	-0.05	#	0.08	0.17	0.10	-	-	-	-	0.74	-	-	-	-	-
Importance.of.the.cost.of.implementing.green.logistics	-0.11	-0.02	-0.01	0.09	0.40	0.09	#	0.38	0.09	0.23	-	-	-	-	0.40	-	-	-	-	-
Importance.of.international.agreements	0.15	0.15	0.04	0.01	0.11	0.04	#	0.05	0.12	0.77	-	-	-	-	-	-	-	-	-	0.77
Importance.of.information.and.business.analytics.create.a.competitive.advantage	0.13	0.60	-0.13	0.08	0.22	-0.12	#	0.26	-0.13	0.32	-	0.60	-	-	-	-	-	-	-	-
Impact.of.domestic.and.environmental.policies	-0.33	-0.03	-0.04	0.24	0.53	0.10	#	0.30	-0.02	0.04	-	-	-	-	0.53	-	-	-	-	-
Importance.of.customers.awareness	-0.03	0.45	-0.10	0.15	0.38	0.27	#	-0.01	-0.10	0.23	-	0.45	-	-	-	-	-	-	-	-
impact..of.big.data.tools.for.sustainability.	-0.09	0.72	0.08	-0.02	0.12	-0.02	#	-0.27	-0.06	0.29	-	0.72	-	-	-	-	-	-	-	-
How.has.your.access.to.useful.data.changed.during.the.past.year.....	0.11	0.11	0.21	-0.10	0.16	-0.17	#	0.11	0.44	0.01	-	-	-	-	-	-	-	-	0.44	-
How.often.do.you.feel.you.have.the.right.data.needed.to.make.key.business.decis	-0.07	0.14	-0.06	-0.17	0.03	0.04	#	0.01	0.86	0.12	-	-	-	-	-	-	-	-	0.86	-
Data.is.timely	-0.30	-0.19	0.15	0.17	0.25	0.10	#	0.03	0.22	0.06	-	-	-	-	-	-	-	-	-	-
Data.is.Relevant	0.29	-0.18	0.17	-0.14	0.26	0.30	#	0.34	-0.03	-0.22	-	-	-	-	-	-	-	-	-	-
Data.is.Reliable	0.26	-0.02	0.07	0.09	0.32	0.18	#	-0.03	0.41	0.08	-	-	-	-	-	-	-	-	0.41	-
Data.is.Accessible	0.02	0.06	0.05	-0.41	0.42	-0.06	#	0.02	0.03	0.03	-	-	-	-0.41	0.42	-	-	-	-	-
Data.is.Consistent	0.07	0.01	0.33	-0.02	0.09	0.37	#	-0.25	0.29	0.09	-	-	-	-	-	-	-	-	-	-
Data.is.Complete	-0.11	0.17	0.20	-0.01	0.44	0.14	#	-0.05	-0.09	-0.19	-	-	-	-	0.44	-	-	-	-	-
just.began.to.apply.analytics	0.12	0.10	0.11	-0.23	-0.04	0.25	#	0.76	-0.12	-0.14	-	-	-	-	-	-	-	0.76	-	-
aren.t.sure	0.01	-0.19	-0.18	0.24	0.14	-0.35	#	-0.17	0.36	0.09	-	-	-	-	-	-	-0.50	-	-	-
haven.t.acted	0.10	0.32	-0.17	-0.16	-0.28	0.11	#	0.18	0.22	0.14	-	-	-	-	-	-	-	-	-	-
do.not.use.analytics.to.drive.strategic.decisions.	0.13	0.16	0.25	0.20	0.14	0.18	#	-0.42	-0.09	-0.33	-	-	-	-	-	-	-	-0.42	-	-
We.are.using.analytics..but.so.are.our.competitors.	0.09	-0.09	0.05	-0.06	-0.07	0.17	#	-0.26	0.08	0.15	-	-	-	-	-	-	0.74	-	-	-
Analytics.is.not.a.priority.for.senior.management.	0.36	0.12	-0.83	0.07	0.02	0.04	#	0.02	0.09	-0.04	-	-	-0.83	-	-	-	-	-	-	-
Staff.doing.the.input.need.to.know.more.about.the.end.results	0.17	-0.21	0.23	-0.24	0.14	-0.03	#	-0.27	0.30	0.17	-	-	-	-	-	-	-	-	-	-
Analytics.help.improving.innovation	0.12	-0.04	0.74	0.01	-0.07	0.18	#	-0.02	-0.06	0.13	-	-	0.74	-	-	-	-	-	-	-
Your.organization.uses.customer.feedback.to.inform.decision.making	0.16	0.17	-0.07	0.06	0.26	0.01	#	-0.06	-0.01	-0.34	-	-	-	-	-	-	0.72	-	-	-
Use.of.detailed.data.to.tailor.specific.offerings.to.customers	-0.28	0.21	0.10	0.07	0.15	-0.28	#	0.19	0.03	0.24	-	-	-	-	-	-	0.64	-	-	-
Customers.are.engaged.with.your.organization	-0.10	-0.19	0.14	0.27	0.01	-0.04	#	0.29	0.31	-0.04	-	-	-	-	-	-	0.50	-	-	-
Customer.intelligence.has.improved.since.last.year	-0.18	0.13	0.55	0.22	-0.26	-0.17	#	-0.03	0.16	-0.24	-	-	0.55	-	-	-	-	-	-	-
Effectiveness.of.lean.processes.and.cutting.of.wastes	0.21	0.63	0.13	-0.27	-0.07	0.14	#	0.00	0.28	-0.18	-	0.63	-	-	-	-	-	-	-	-
Green.Purchasing.helps.sustainability	-0.03	0.74	-0.03	0.00	-0.14	0.16	#	0.01	0.11	-0.08	-	0.74	-	-	-	-	-	-	-	-
Would.you.....use.BDPA.to.turn.your.purchasing.more.green.or.sustainable..	0.34	-0.14	-0.09	0.79	-0.08	0.25	#	-0.10	0.06	0.02	-	-	-	0.79	-	-	-	-	-	-
Would.you.....implement.BDPA.if.it.could.improve.your.purchasing..	-0.08	0.13	-0.17	0.56	0.18	-0.13	#	0.00	-0.12	-0.22	-	-	-	0.56	-	-	-	-	-	-
Would.you.....implement.BDPA.if.it.could.make.your.company.more.green..	-0.12	0.05	0.16	0.83	0.03	-0.04	#	-0.05	-0.24	0.06	-	-	-	0.83	-	-	-	-	-	-

Annex c:

“THE COMPANY A” flowchart processes.

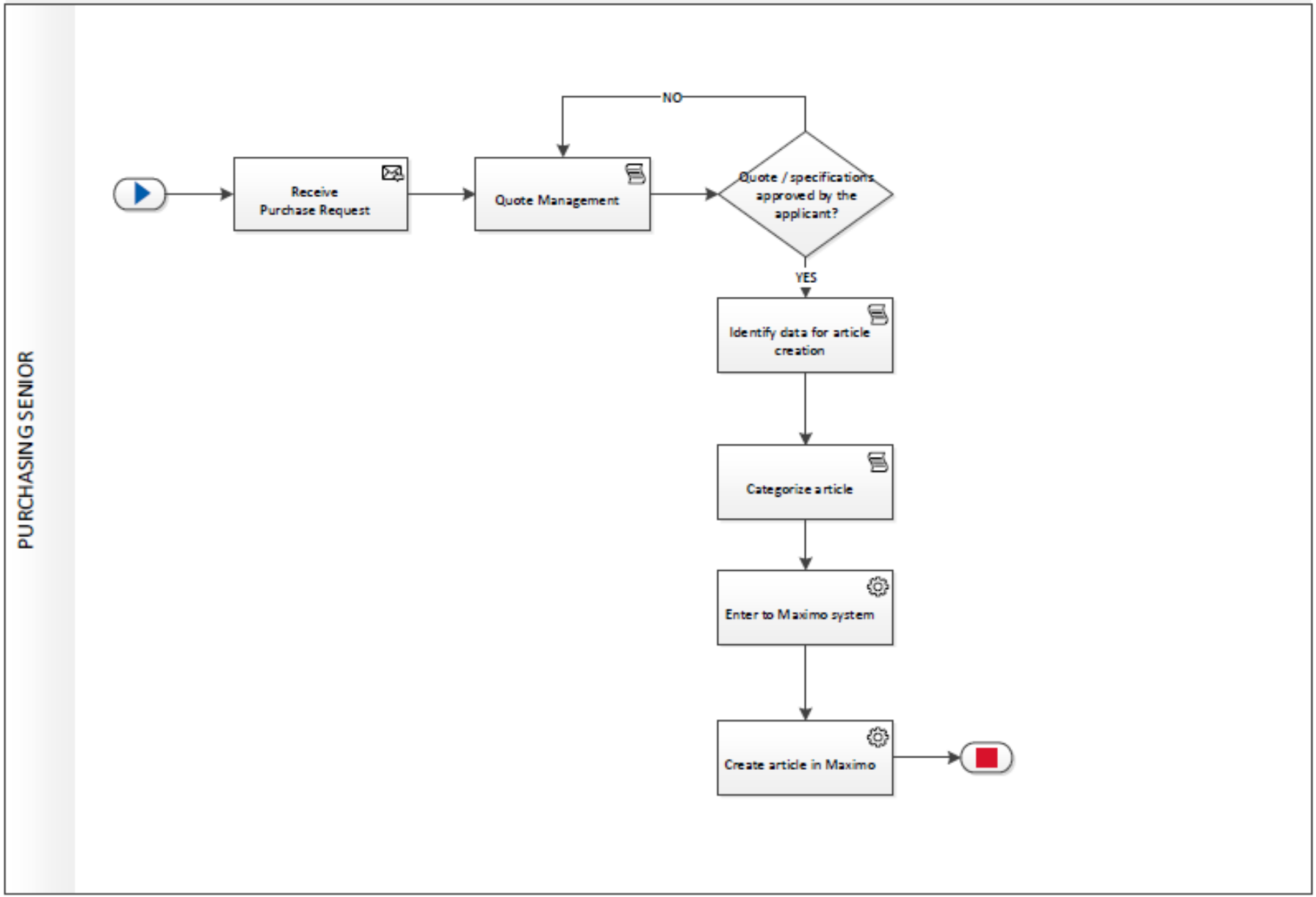
Purchasing Process

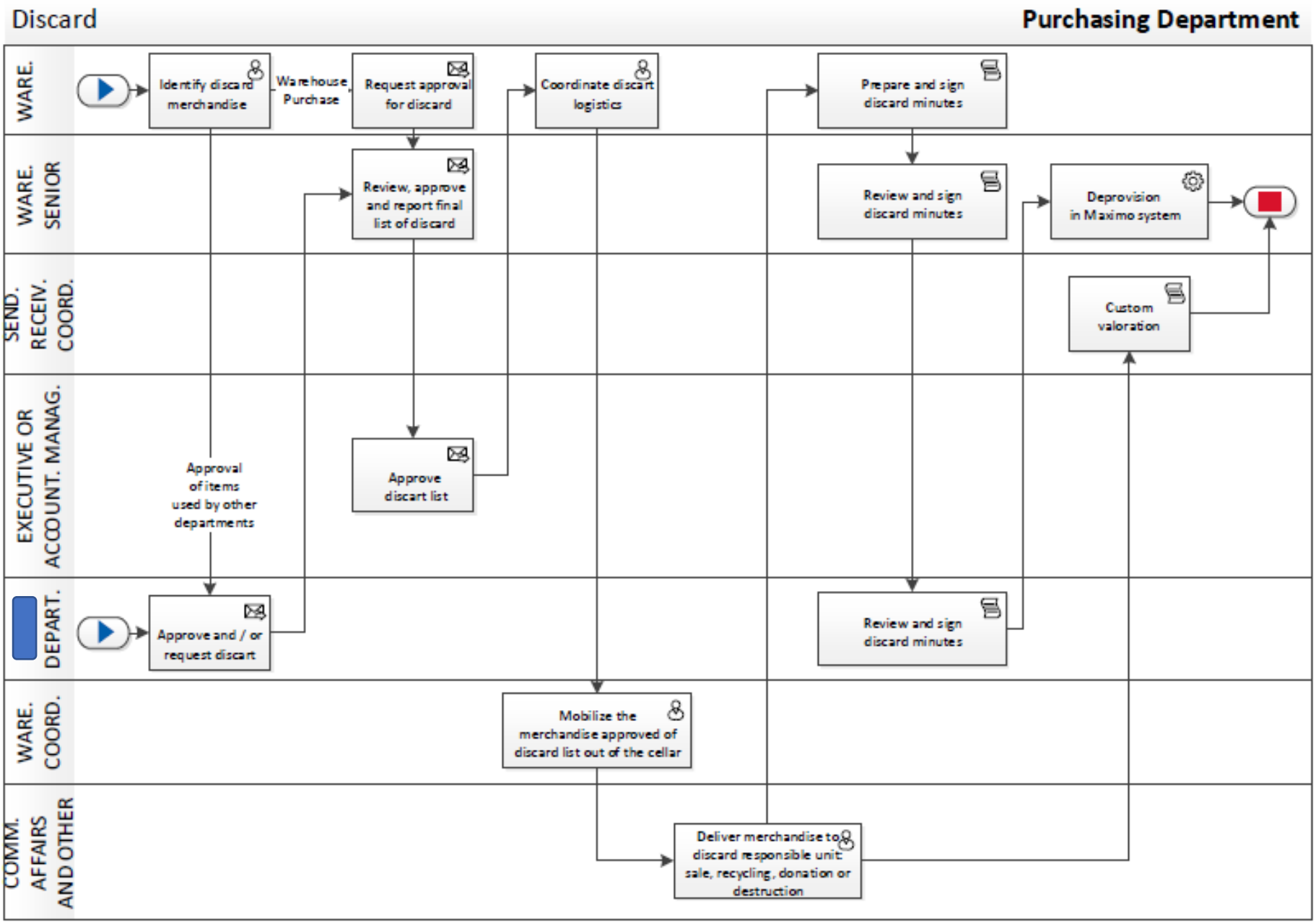
Purchasing Department

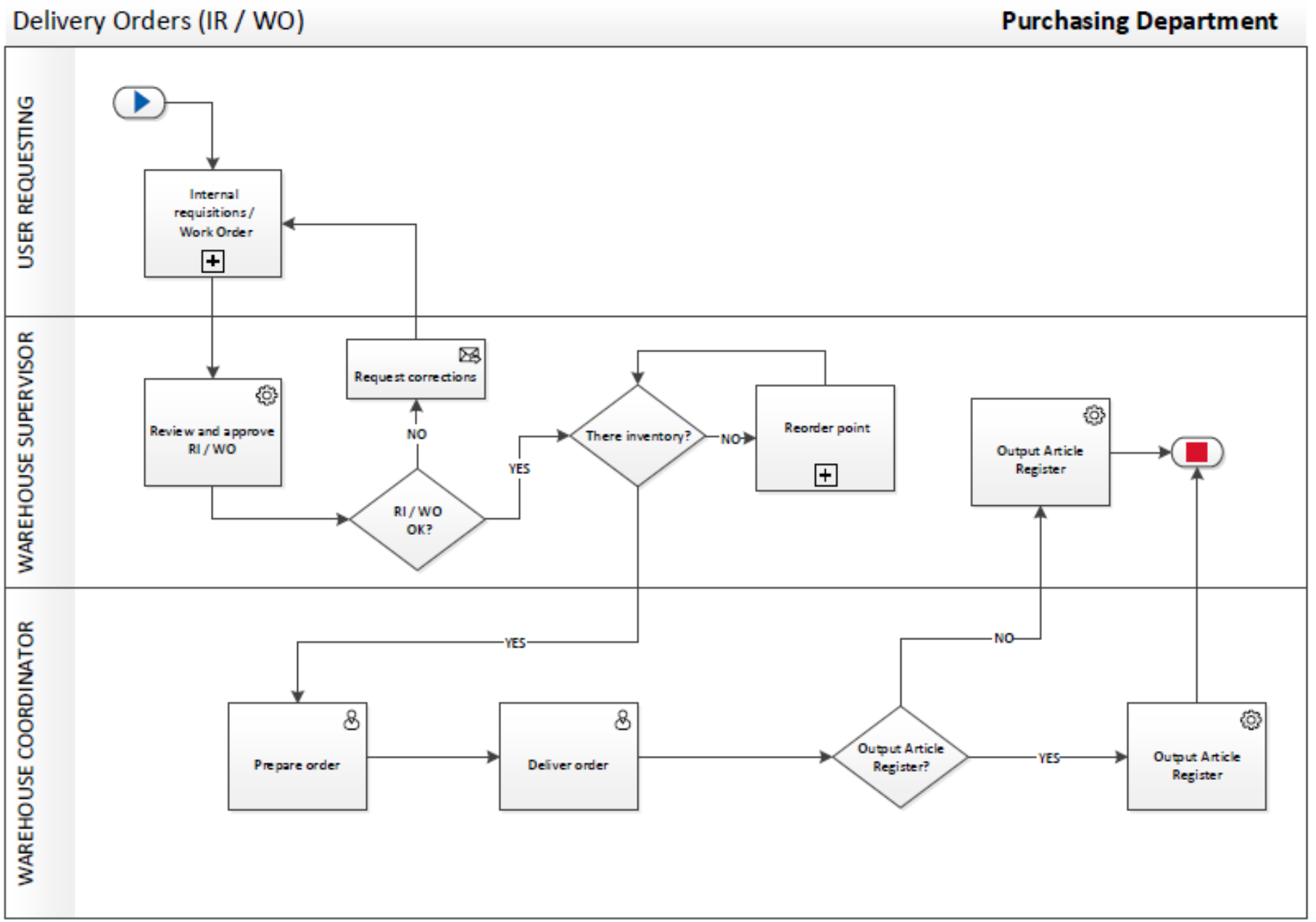


Item Creation

Purchasing Department

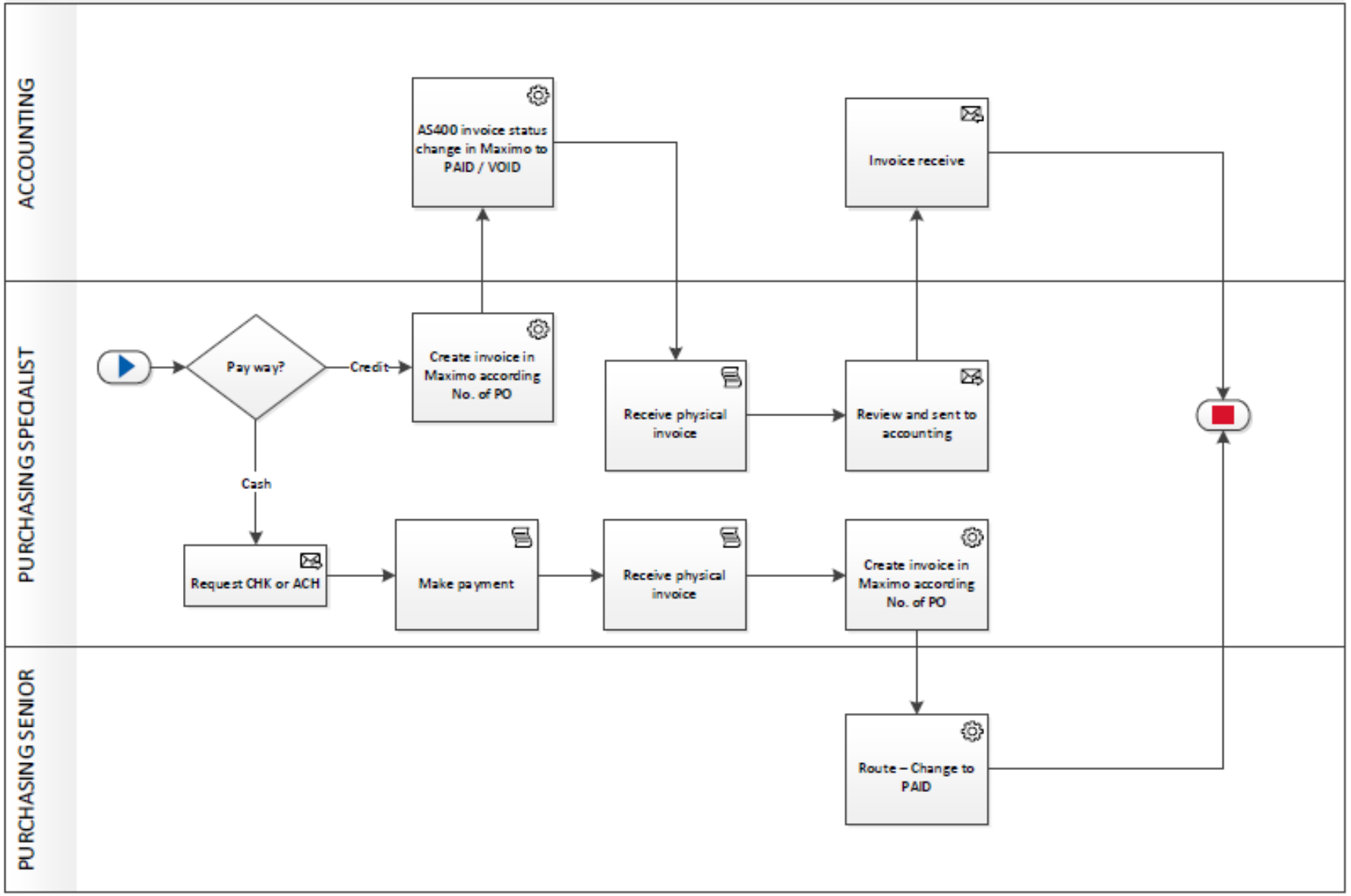



Discard
Purchasing Department
WARE.
WARE. SENIOR
SEND. RECEIV. COORD.
EXECUTIVE OR ACCOUNT. MANAG.
DEPART.
WARE. COORD.
COMM. AFFAIRS AND OTHER
Identify discard merchandise
Warehouse, Purchase
Request approval for discard
Coordinate discart logistics
Prepare and sign discard minutes
Review, approve and report final list of discard
Review and sign discard minutes
Deprovision in Maximo system
Custom valoration
Approval of items used by other departments
Approve discart list
Approve and / or request discart
Review and sign discard minutes
Mobilize the merchandise approved of discard list out of the cellar
Deliver merchandise to discard responsible unit: sale, recycling, donation or destruction


Delivery Orders (IR / WO)
Purchasing Department
USER REQUESTING
WAREHOUSE SUPERVISOR
WAREHOUSE COORDINATOR
Internal requisitions / Work Order
Review and approve RI / WO
Request corrections
NO
RI / WO OK?
YES
There inventory?
NO
Reorder point
Output Article Register
YES
Prepare order
Deliver order
Output Article Register?
NO
YES
Output Article Register

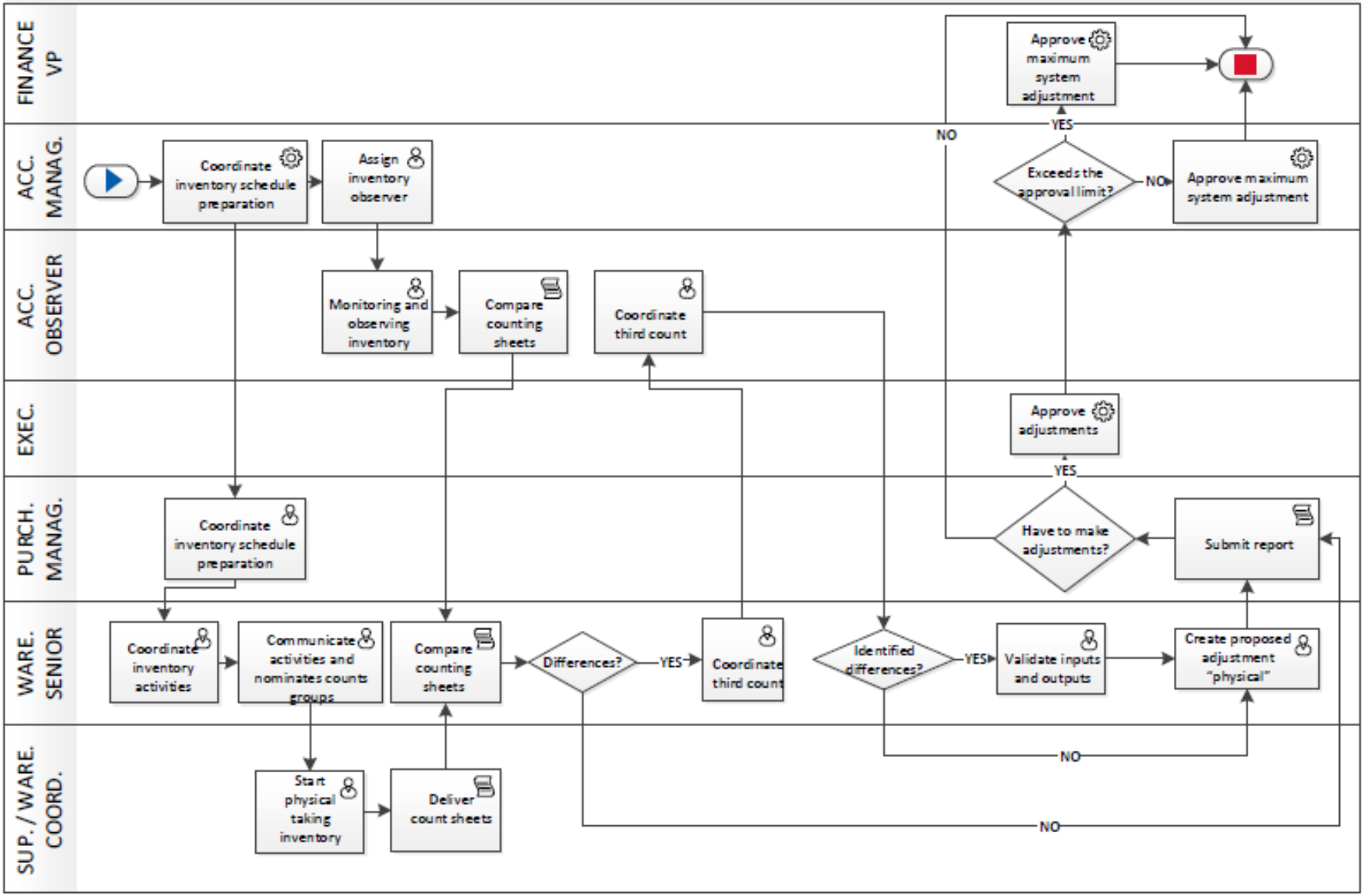
Invoicing

Purchasing Department



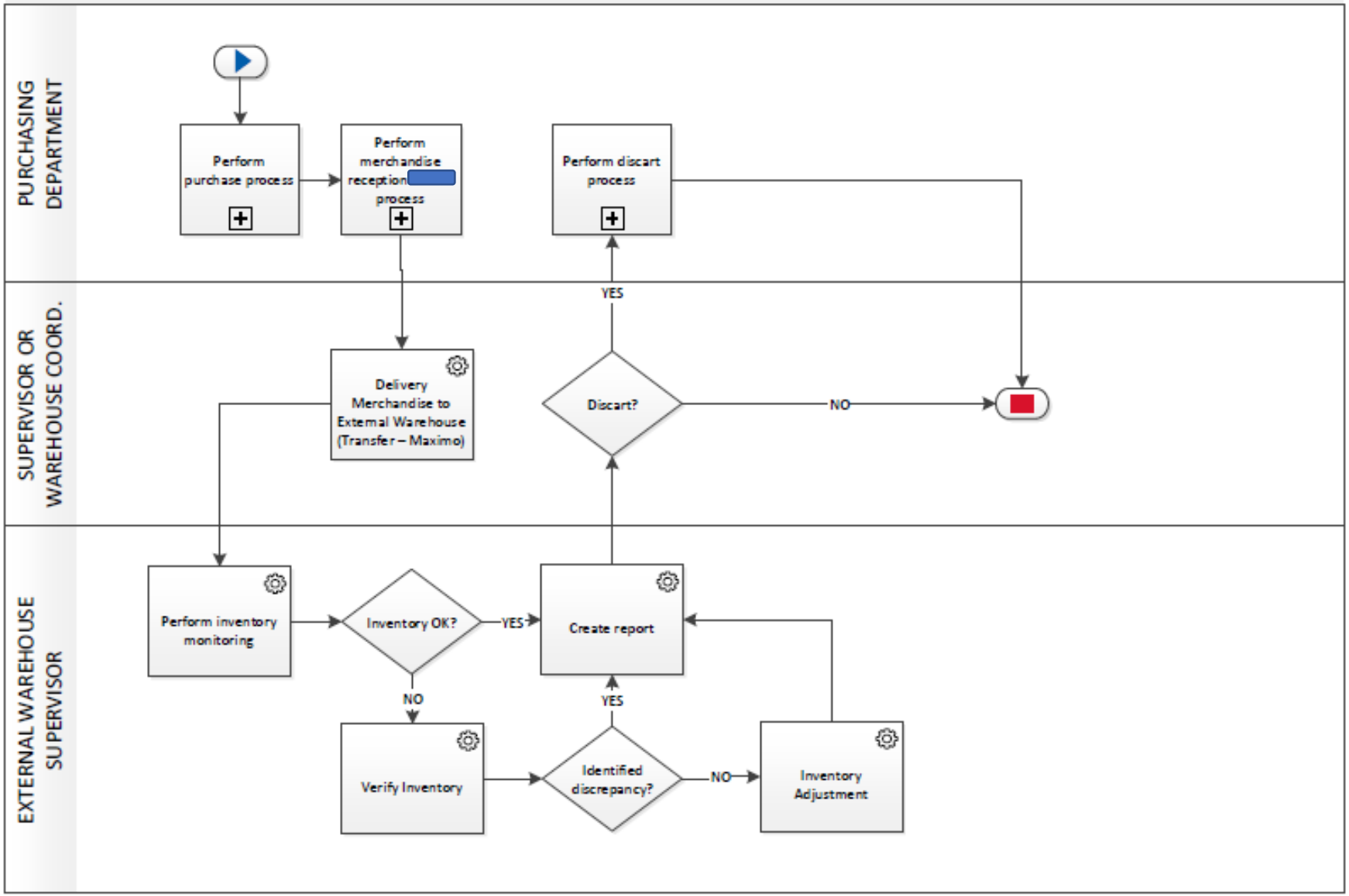
Inventory and settings

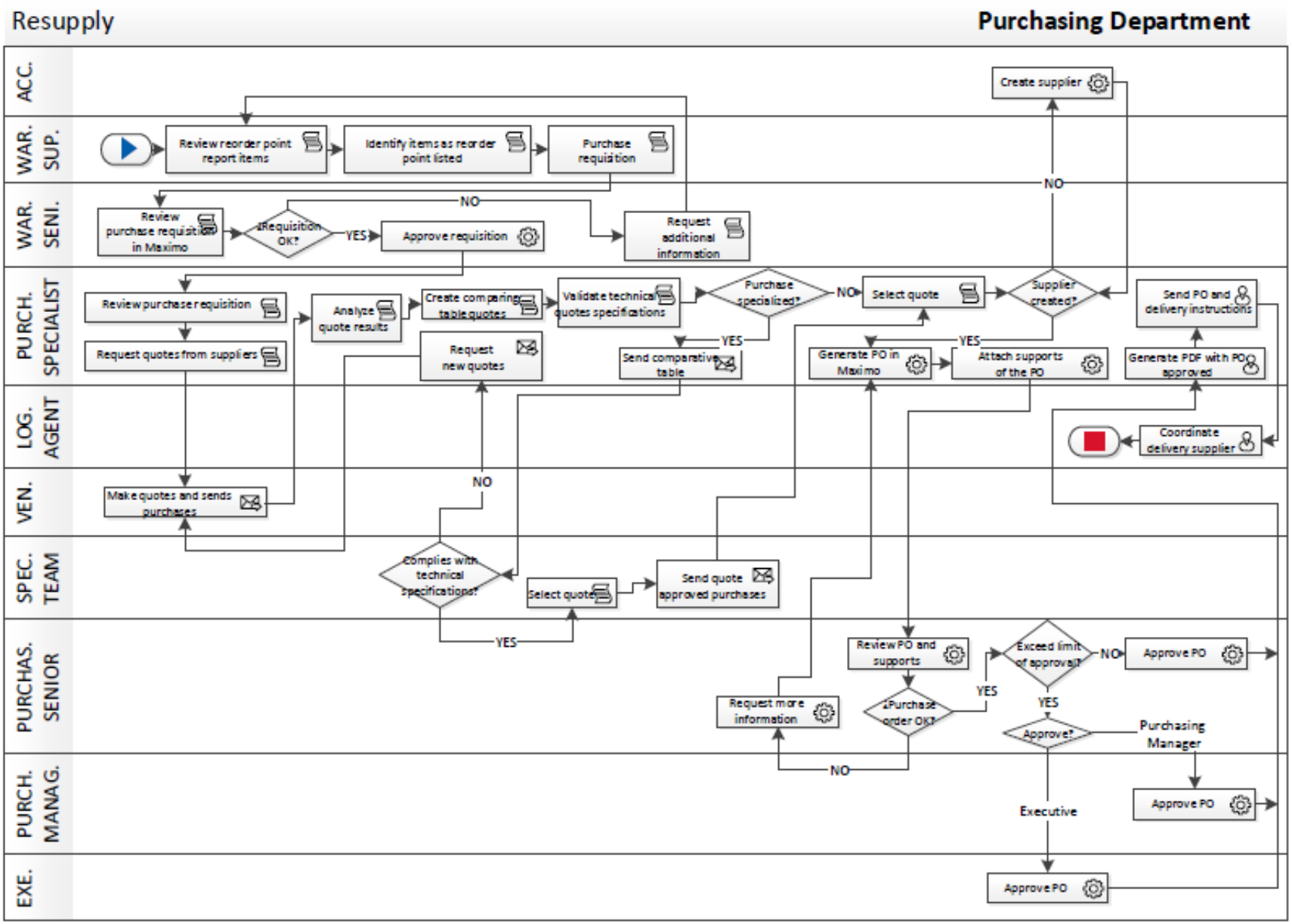
Purchasing Department

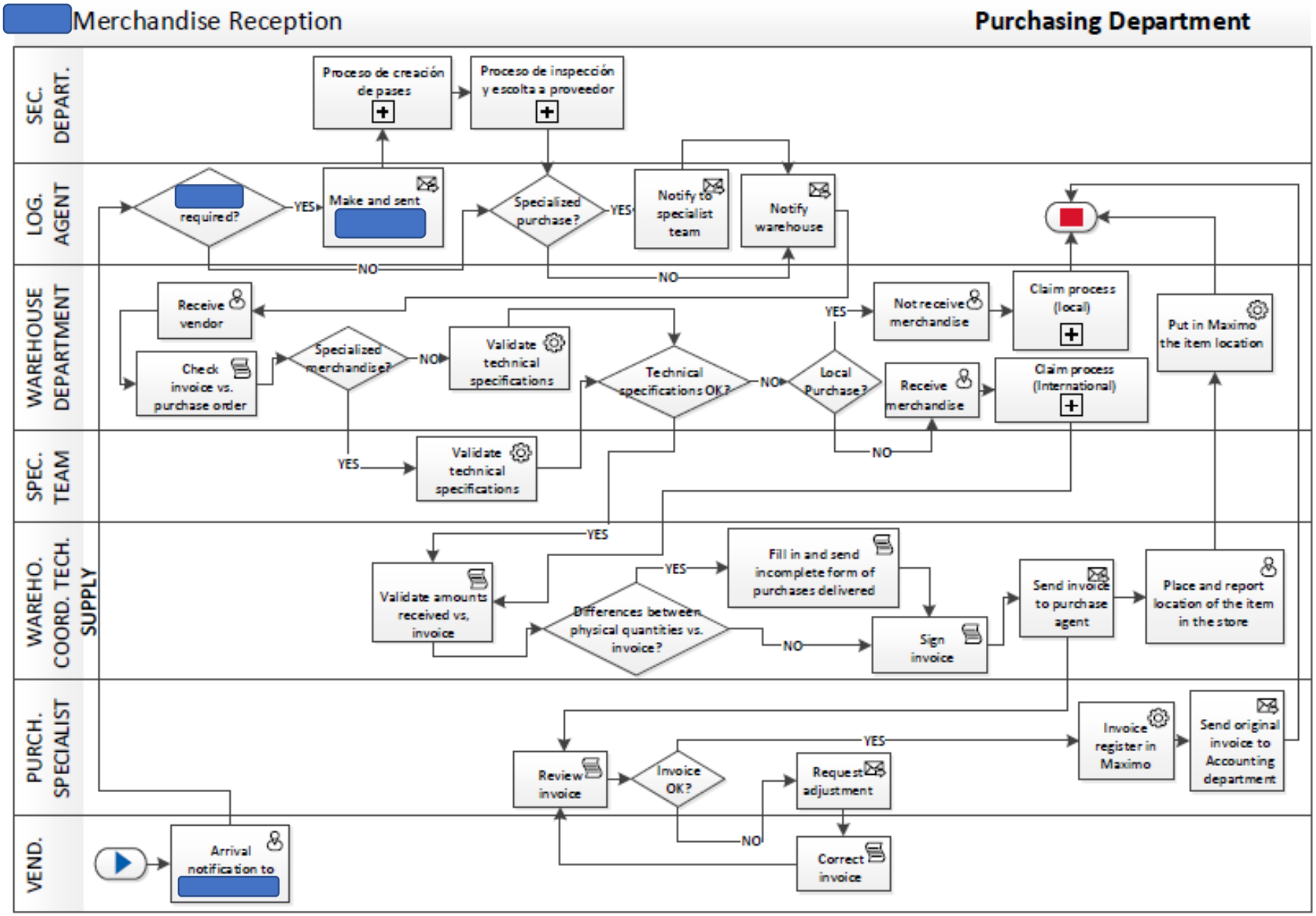


External Warehouse Process

Purchasing Department

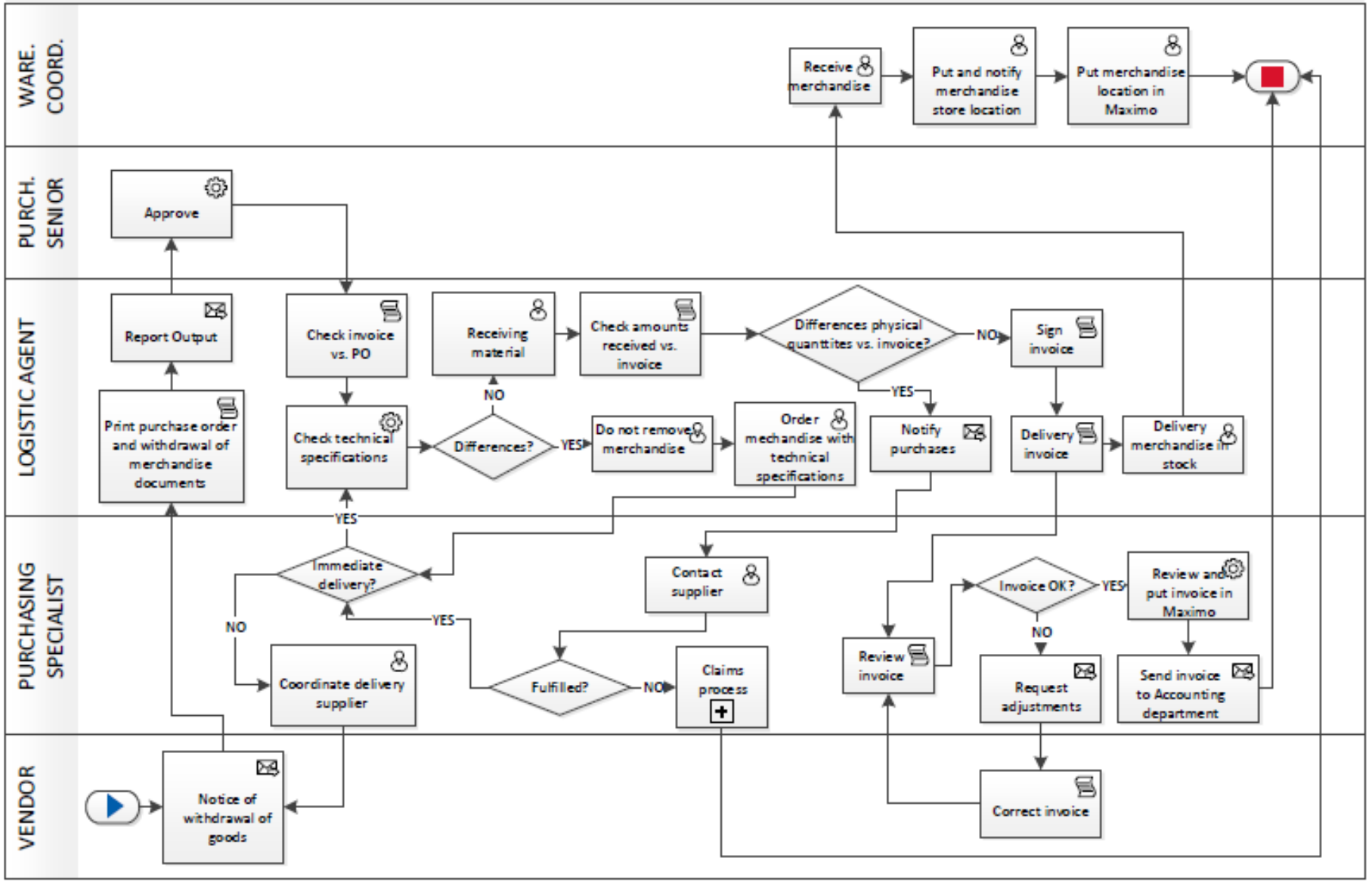


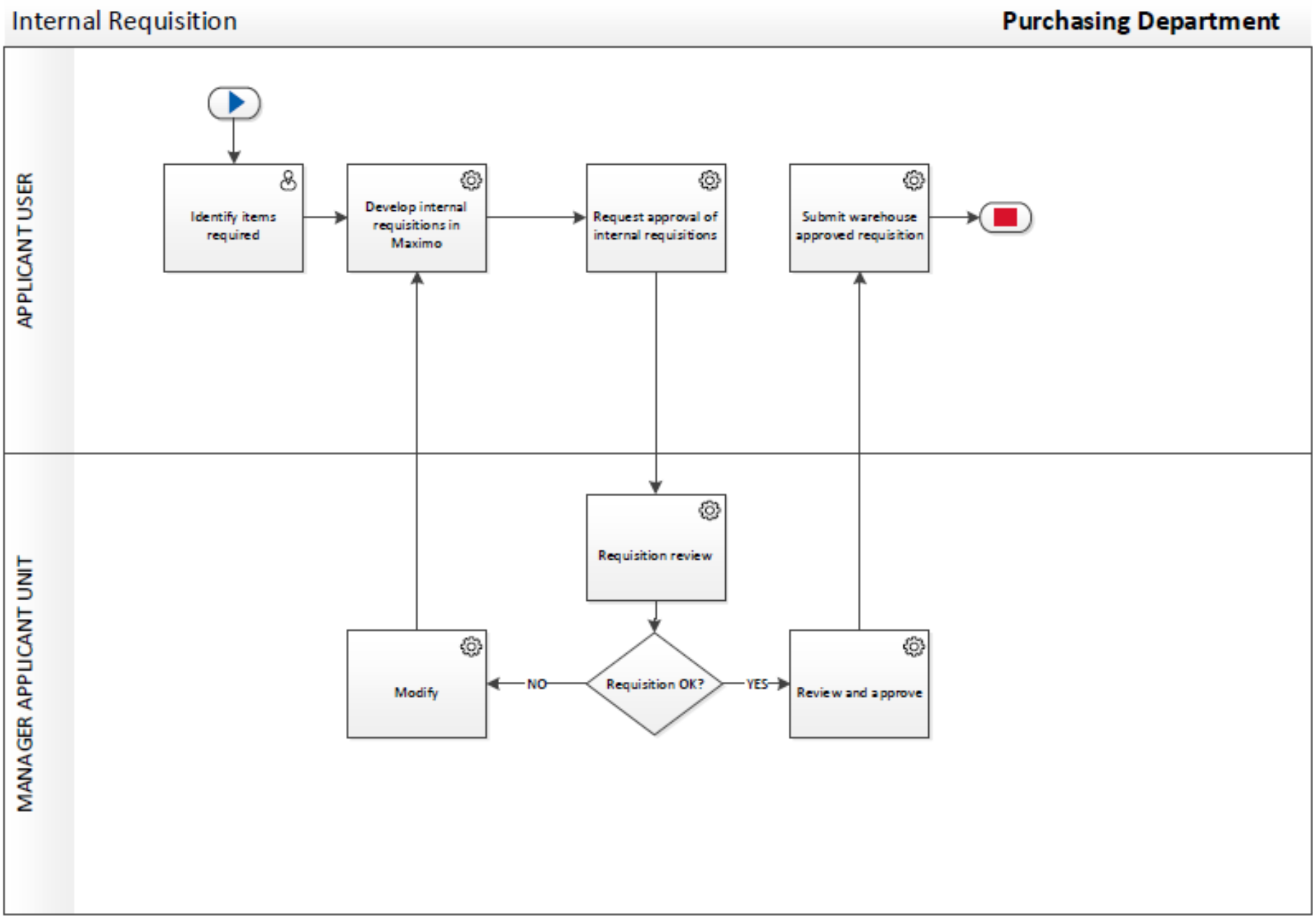

Resupply
Purchasing Department
ACC.
WAR. SUP.
WAR. SENI.
PURCH. SPECIALIST
LOG. AGENT
VEN.
SPEC. TEAM
PURCHAS. SENIOR
PURCH. MANAG.
EXE.
Create supplier
Review reorder point report items
Identify items as reorder point listed
Purchase requisition
NO
Review purchase requisition in Maximo
¿Requisition OK?
YES
Approve requisition
Request additional information
Review purchase requisition
Analyze quote results
Create comparing table quotes
Validate technical quotes specifications
Purchase specialized?
NO
Select quote
Supplier created?
Send PO and delivery instructions
Request quotes from suppliers
Request new quotes
Send comparative table
YES
Generate PO in Maximo
Attach supports of the PO
Generate PDF with PO approved
Coordinate delivery supplier
Make quotes and sends purchases
NO
Complies with technical specifications?
Select quote
Send quote approved purchases
YES
Review PO and supports
Exceed limit of approval?
NO
Approve PO
Request more information
¿Purchase order OK?
YES
YES
Approve?
Purchasing Manager
NO
Approve PO
Executive
Approve PO


Merchandise Reception
Purchasing Department
SEC. DEPART.
LOG. AGENT
WAREHOUSE DEPARTMENT
SPEC. TEAM
WAREHO. COORD. TECH. SUPPLY
PURCH. SPECIALIST
VEND.
Proceso de creación de pases
Proceso de inspección y escolta a proveedor
required?
YES
Make and sent
Specialized purchase?
YES
Notify to specialist team
Notify warehouse
NO
NO
Receive vendor
Check invoice vs. purchase order
Specialized merchandise?
NO
Validate technical specifications
Technical specifications OK?
NO
Local Purchase?
YES
Not receive merchandise
Claim process (local)
Put in Maximo the item location
Receive merchandise
Claim process (International)
NO
YES
Validate technical specifications
YES
Validate amounts received vs, invoice
YES
Differences between physical quantities vs. invoice?
Fill in and send incomplete form of purchases delivered
NO
Sign invoice
Send invoice to purchase agent
Place and report location of the item in the store
Review invoice
Invoice OK?
YES
Request adjustment
NO
Correct invoice
Invoice register in Maximo
Send original invoice to Accounting department
Arrival notification to

Supplier Receiving Merchandise

Purchasing Department




Internal Requisition
Purchasing Department
APPLICANT USER
MANAGER APPLICANT UNIT
Identify items required
Develop internal requisitions in Maximo
Request approval of internal requisitions
Submit warehouse approved requisition
Requisition review
Modify
NO
Requisition OK?
YES
Review and approve

Titre : **Investigation qualitative des facteurs qui permettent l'analyse de Big Data et la chaîne d'approvisionnement**

Mots clés : Durabilité, Analyse de la Chaîne d'Approvisionnement Big Data et Analyse Prédictive, Facteurs

Résumé : Les académiques et les professionnels ont déjà montré que le Big Data et l'analyse prédictive, également connus dans la littérature sous le nom de BDPA, peuvent jouer un rôle fondamental dans la transformation et l'amélioration des fonctions de l'analyse de la chaîne d'approvisionnement durable (SSCA). Cependant, les connaissances sur la meilleure manière d'utiliser la BDPA pour augmenter simultanément les performances sociales, environnementale et financière. Par conséquent, avec les connaissances tirées de la littérature sur la SSCA, il semble que les entreprises peinent encore à mettre en œuvre les pratiques de la SSCA. Les chercheurs conviennent qu'il est encore nécessaire de comprendre les techniques, outils et facteurs des concepts de base de la SSCA pour adoption. C'est encore plus important d'intégrer BDPA en tant qu'atout stratégique dans les activités commerciales. Par conséquent, cette étude examine, par exemple, quels sont les facteurs de SSCA et quels sont les outils et techniques de BDPA qui permettent de mettre en évidence le 3BL (pour ses abréviations en anglais : "triple bottom line") des rendements de durabilité (environnementale, sociale et financière) via SCA.

La thèse a adopté un constructionniste modéré, car elle comprend l'impact des facteurs Big Data sur les applications et les indicateurs de performance de la chaîne logistique analytique et durable. La thèse a également adopté un questionnaire et une étude de cas en tant que stratégie de recherche permettant de saisir les différentes perceptions des personnes et des entreprises dans l'application des mégadonnées sur la chaîne d'approvisionnement analytique et durable. La thèse a révélé une meilleure vision des facteurs pouvant influencer l'adoption du Big Data dans la chaîne d'approvisionnement analytique et durable. Cette recherche a permis de déterminer les facteurs en fonction des variables ayant une incidence sur l'adoption de BDPA pour SSCA, des outils et techniques permettant la prise de décision via SSCA et du coefficient de chaque facteur pour faciliter ou retarder l'adoption de la durabilité. Il n'a pas été étudié avant. Les résultats de la thèse suggèrent que les outils actuels utilisés par les entreprises ne peuvent pas analyser de grandes quantités de données par eux-mêmes. Les entreprises ont besoin d'outils plus appropriés pour effectuer ce travail

Title: **A qualitative analysis to investigate the enablers of big data analytics that impacts sustainable supply chain**

Keywords: sustainability, sustainable supply chain, big data and predictive analytics, enablers

Abstract: Scholars and practitioners already shown that Big Data and Predictive Analytics also known in the literature as BDPA can play a pivotal role in transforming and improving the functions of sustainable supply chain analytics (SSCA). However, there is limited knowledge about how BDPA can be best leveraged to grow social, environmental and financial performance simultaneously. Therefore, with the knowledge coming from literature around SSCA, it seems that companies still struggled to implement SSCA practices. Researchers agree that is still a need to understand the techniques, tools, and enablers of the basics SSCA for its adoption; this is even more important to integrate BDPA as a strategic asset across business activities. Hence, this study investigates, for instance, what are the enablers of SSCA, and what are the tools and techniques of BDPA that enable the triple bottom line (3BL) of sustainability performances through SCA.

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The thesis adopted moderate constructionism since understanding of how the enablers of big data impacts sustainable supply chain analytics applications and performances. The thesis also adopted a questionnaire and a case study as a research strategy in order to capture the different perceptions of the people and the company on big data application on sustainable supply chain analytics.

The thesis revealed a better insight of the factors that can affect in the adoption of big data on sustainable supply chain analytics. This research was capable to find the factors depending on the variable loadings that impact in the adoption of BDPA for SSCA, tools and techniques that enable decision making through SSCA, and the coefficient of each factor for facilitating or delaying sustainability adoption that wasn't investigated before. The findings of the thesis suggest that the current tools that companies are using by itself can't analyses data. The companies need more appropriate tools for the data analysis.