Universidade do Minho
Escola de Engenharia

Miguel Jorge Teixeira Brandão de Carvalho

Monitoring supplier deliveries and analysis of potential risk factors in supply chain management: A Business Intelligence and Analytics approach

julho de 2021

Monitoring supplier deliveries and analysis
of potential risk factor in supply chain management:
A Business Intelligence and Analytics approach

Miguel Jorge Teixeira Brandão de Carvalho

UMinho | 2021

Universidade do Minho
Escola de Engenharia

Miguel Jorge Teixeira Brandão de Carvalho

Monitoring supplier deliveries and analysis of potential risk factors in supply chain management: A Business Intelligence and Analytics approach

Dissertação de Mestrado
Mestrado Integrado em Engenharia e Gestão Industrial

Trabalho efetuado sob a orientação do
Professor Doutor Paulo Alexandre da Costa Araújo Sampaio

julho de 2021

Acknowledgements

"We must find time to stop and thank the people who make a difference in our lives." – John F. Kennedy.

My life has been full of great moments and experiences. I have been privileged to have great people by my side, who have made me who I am. Without them, the chapter I am about to end would not have been possible.

Firstly, to professor Paulo Sampaio, for all the inputs, feedback, advice and ideas, and for encouraging me to achieve the most ambitious goals and get the best out of this work.

To Francisco Antunes, a person with immense vision and an amazing mindset, for all the teachings, guidance and attention he gave during my first times at Bosch.

To Sofia Pereira, my supervisor, I thank her for all the ideas, feedback, constant motivation and guidance, and for encouraging me to put everything I have in what I do and aim for perfection.

To ally my colleagues at the Bosch Logistics department. To all the LOS team, especially, João Leite and João Patrício, for all the feedback, support and teachings. To Jorge Guedes, not only for the contributions, ideas and hours spent in this project but also for his fellowship. To all the former CM/LOI and BrgP/LOI colleagues, for all the good moments. To Ana Morais, who has been guiding and teaching me so much during my new adventure at BrgP/LOI. A special thank you to Marta and Matilde, who have been great friends and supported me from the beginning. To João Gonçalves and Rui Machado, for the support, help, encouragement, but more importantly, for the friendship that has been built and all the *"engodo"* talks.

To all my friends and colleagues from university, for the amazing years spent together. A special thank you to the *Trouxas*, Xano, Gonçalo, Hugo, Ramires and Pedro, for all the dinners, beers and adventures. To Zé, Mariana, Mónica, Inês and Lili, for the genuine and long-lasting friendship. To all the *Incendiários*, for the great moments and fires started. A special thank you to Bruno Alcaide, for the friendship and great times.

To all my family, for all the fun and always enjoyable moments provided throughout the years. It is unfair to not mention each one individually, but know that I am truly grateful to each and every one of you. A special thank you to my godmother, *tia* Sameiro, for all the encouragement, care and guidance. To Pedro, for all the companionship and great moments spent together throughout 24 years. To my goddaughter, Francisca, and her brother, Henrique, for all the joy they bring to someone even on the worst day. To her parents and sister, for the opportunity to play such an important role in their life.

To my dear sister who, despite all the fighting, is a great friend and partner for nonsense stuff. May this work inspire her to follow her dreams, but never serve as an example, as each person has its own story and path.

To my parents, for the opportunities provided throughout my life. For all the support, care and education. For providing everything I needed and making sure that I never lacked anything. I hope this work has made them proud and have the feeling of "mission accomplished". Also, thank you for not charging any rent, which is nice given the housing prices. I dedicate this dissertation to them – together with my grandmothers, who did not have the chance to witness this academic journey and its culmination, but I believe would have been tremendously proud and happy with this moment.

To Dani, for all the support, motivation, care. For being a great partner in the past years. For being a source of inspiration and for always encouraging me to reach my dreams and never give up. Thank you for being my rock and safe haven.

"Estes anos são viagem" e *"Todo o destino é partir"*. Well, I leave with a sense of accomplishment and happiness, as I have enjoyed and made the most of this amazing journey.

STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration.

I further declare that I have fully acknowledged the Code of Ethical Conduct of the University of Minho.

Resumo

Atualmente, a crescente concorrência do mercado apresenta às empresas novos e mais complexos desafios, exigindo-lhes uma maior capacidade de resposta e agilidade, e assim, implementar práticas de gestão da cadeia de abastecimento (GCA). A gestão de encomendas e abastecimento de material é o subcampo da GCA responsável pela gestão de encomendas de material e monitorização das entregas de fornecedor. No entanto, a gestão de encomendas e fornecimento de material não é uma tarefa fácil e está sujeita a falhas e dificuldades. Um problema que pode surgir são os envios em avanço, ou seja, quando os fornecedores entregam as os materiais antes da data solicitada.

O trabalho apresentado nesta dissertação aborda o problema da monitorização de envios em avanço, enfrentado pela Bosch Braga. Os envios em avanço causam graves complicações à empresa, como o aumento dos custos de compra e dos níveis de stock, o que possivelmente compromete a gestão da ocupação do armazém. Actualmente, a empresa é incapaz de detetar os envios em avanço, o que torna difícil tomar rapidamente medidas que atenuem o impacto ou impeçam a sua ocorrência no futuro.

Para enfrentar o problema, são levadas a cabo diferentes acções numa tentativa de encontrar uma solução. Ao fazer uso dos dados disponíveis, é desenvolvida uma solução de *Business Intelligence and Analytics* (BI&A). A solução recolhe dados de encomendas e de entregas e identifica materiais em trânsito que estão a ser enviados em avanço. A solução permite à empresa monitorizar as entregas dos fornecedores e detectar desvios nas entrega assim que os materiais começam o seu transporte. Para apoiar a solução e ajudar na análise os envios em avanço, é também criado um processo de análise.

As soluções desenvolvidas alcançaram bons resultados, reduzindo a quantidade e o valor dos envios em avanço, a ocupação do armazém, o valor total das mercadorias em trânsito e os níveis de stock. Isto apresenta evidências de que a utilização de BI&A pode ajudar a melhorar a GCA.

Simultaneamente, é realizado um estudo para identificar potenciais fatores de risco que afectam o desempenho dos fornecedores e levam à ocorrência de envios em avanço. São analisadas várias variáveis, resultando na detecção de tendências no desempenho dos fornecedores, permitindo uma melhor compreensão dos factores que influenciam os envios em avanço. Acredita-se que este trabalho acrescenta à literatura conhecimento sobre os envios em avanço e o sobre a adopção de BI&A na GCA.

Palavras-Chave

Análise de dados, Entrega atempada de fornecedores, Gestão da Cadeia de Abastecimento, Gestão do Abastecimento, Inteligência de Negócio

ABSTRACT

Nowadays, the increasing market competition presents companies with new and more complex challenges, requiring them to have greater responsiveness and agility, and thus, implement supply chain management (SCM) practices. Material order and supply management is the subfield of SCM responsible for material order management and supplier delivery monitoring. However, material order and supply management is not an easy task and is subject to failures and difficulties. One problem that may arise is the occurrence of early deliveries, i.e., when suppliers deliver goods before the actual requested date.

The work presented in this dissertation addresses the problem of early deliveries monitoring, faced by Bosch Braga. Early deliveries cause significant complications to the company, such as the increase of purchasing costs and stock levels, which possibly compromises warehouse occupation management. Currently, the company is unable to detect early deliveries, which makes it difficult to take actions quickly that mitigate the impact or prevent it from happening in the future.

To tackle the problem, different actions are carried out in an attempt to find a solution. By making use of the available data, a Business Intelligence and Analytics (BI&A) solution is developed. The solution collects orders and deliveries data and identifies materials in transit that are being sent earlier than requested. The solution allows the company to monitor supplier deliveries and detect delivery deviations as soon as materials start their transport. To support the solution and assist in the analysis of the early deliveries, an analysis process is also created, assisting the decision-making process.

The solutions developed achieved good results, reducing the amount and value of early deliveries, warehouse occupation, the total value of goods in transit and the stock levels. This presents evidence that the use of BI&A can help improve supply chain operations.

Simultaneously, a study is conducted to identify potential risk factors that affect suppliers performance and lead to the occurrence of early deliveries. Different variables are analysed, resulting in the detection of trends and patterns in suppliers performance, thus generating a better understanding of the factors influencing early deliveries. It is believed that this work contributes to the literature by creating some knowledge about supplier early deliveries and the benefits of the adoption of BI&A in SCM.

KEYWORDS

Business Intelligence, Data Analytics, Supplier On-time Delivery, Supply Chain Management, Supply Management

TABLE OF CONTENTS

List of Figures

LIST OF TABLES

Acronyms

AE – Automotive Eletronics

AI – Artificial Intelligence

ASN – Advanced Shipping Notice

BA – Business Analytics

BDA – Big Data Analytics

BI – Business Intelligence

BI&A – Business Intelligence and Analytics

BrgP – Bosch Braga Plant

CM – Car Multimedia

DAP – Delivery at Place Incoterm

DAX – Data Analysis Expressions

EDDR – Early Deliveries Detection Report

ERP – Enterprise Resource Planning

ETA – Estimated Time of Arrival

ETD – Estimated Time of Dispatch

ETL – Extract, Transform, Load

FCA – Free Carrier Incoterm

LSP – Logistics Service Provider

MRP – Material Requirement Planning

PN – Part Number

PTF – Planning Time Fence

SAP – Systems Applications and Products in Data Processing

SC – Supply Chain

SCA – Supply Chain Analytics

SCA&I – Supply Chain Analytics and Intelligence

SCM – Supply Chain Management

SQL – Structured Query Language

1. Introduction

This dissertation falls within the scope of the Integrated Masters in Industrial Engineering and Management. The project described throughout this document was carried out at Bosch, in Braga, more specifically in the Procurement team, part of the Logistics department. This section provides an overview of the problem, the used research methodology and research questions, the goals of the project, and the structure of this dissertation.

1.1 Background

Nowadays, the increasing market competition presents companies with new and more complex challenges, requiring them to have greater responsiveness and agility. This requires the implementation of supply chain management (SCM) practices, which has a direct impact on the competitive advantage and organisational performance of companies (S. Li et al., 2006).

According to the Council of Supply Chain Management Professionals (CSCMP), supply chain management "encompasses the planning and management of all activities involved in sourcing and procurement, conversion, and all logistics management activities. Importantly, it also includes coordination and collaboration with channel partners, which can be suppliers, intermediaries, third-party service providers, and customers. In essence, supply chain management integrates supply and demand management within and across companies." (Council of Supply Chain Management Professionals (CSCMP), 2013). This change of perspective, from looking to organisations as isolated entities to a supply chain view is driven by growing customer demand that requires more agile responses. To achieve this, strong coordination of inbound supply chain (SC) processes with suppliers and carriers is needed. With this in mind, organisations are beginning to realise that to deal with the new challenges they face, it is not enough to focus solely on improving internal processes (Prajogo et al., 2012), as competition is not between single companies anymore, but between supply chains (Quang et al., 2016). Operational and business performance depends on supply chain integration (Flynn et al., 2010), and, therefore, being able to work closely and monitor the entire supply chain is crucial for the success of organisations.

Purchasing and supply management is the subfield "that is concerned with the management of external resources - goods, services, capabilities, and knowledge - that are necessary for running, maintaining, and managing the primary and support processes of a firm at the most favourable conditions" (van Weele & van Raaij, 2014). This subfield can be divided into two major functions, with different stages in each: strategic procurement, responsible for major strategic decisions such as defining the requirements of the goods to be bought, supplier selection and contracting; and operational procurement, responsible for the operations, order management and delivery monitoring (Carvalho, 2017). The importance of order and supply management is widely recognised, as companies, to fulfil their customers' demand, need to assure they are agile and have the right materials at the right place, at the right time. If a company is unable to guarantee an efficient flow of materials to its facilities, it might compromise and affect its capability to satisfy its customers.

However, material order and supply management is not an easy task and is subject to failures and difficulties, since suppliers do not always deliver according to orders. The most critical problem is likely to be late deliveries since material shortages can disrupt the supply chain, which might have consequences for the company, as it fails to deliver to its customer (Tang, 2006). However, a second problem with deliveries may arise, which is early deliveries. Early deliveries occur when suppliers deliver goods before the actual requested date. This topic has not been studied in the literature and is hardly discussed, as pointed by Peng and Lu (2017) and Schneiderman (1996). Traditionally, early deliveries are not a problem (Schneiderman, 1996), as goods arrive earlier and the risk of delays is reduced. However, early deliveries bring consequences, such as the accumulation of stocks, which might lead to warehouse management issues and extra costs (Peng & Lu, 2017). Keeping this in mind, some companies are beginning to realise that early deliveries, although normally not as big a problem as late deliveries, are also an issue to be tackled (Peng & Lu, 2017; Schneiderman, 1996). Proof of that is Walmart, which has started fining its suppliers for delivering too early as well as too late (Bloomberg, 2017; Boyle, 2017; McKevitt, 2017; MH&L Staff, 2017; Pandolph, 2017) to improve their stock levels and operations.

To guarantee the success of their supply operations, organisations need to monitor and have visibility over their inbound supply chain. Supply chain visibility can be defined as access to high-quality information that describes the state of demand and supply (Williams et al., 2013) and is crucial for organisations to be fully aware of their supply chain and identify potential problems and improvement opportunities. To guarantee the ability to monitor and create visibility over the supply chain, new technologies arise, such as data analytics and business intelligence.

With the increase of complexity in supply chains, it is becoming increasingly difficult for organisations to manage their supply chains. At the same time, more data is being produced. To face the new challenges, it is crucial to capture, aggregate and analyse this data (Sanders, 2016), turning it into information and knowledge, producing valuable insights, and increasing visibility. Business intelligence and analytics (BI&A) are the set of "techniques, technologies, systems, practices, methodologies, and applications that analyse critical business data to help an enterprise better understand its business and market and make timely business decisions" (H. Chen et al., 2012). The application of these to supply chains is referred to by literature as supply chain analytics, which is the use of information and analytical tools to make better decisions regarding supply chain flows (Souza, 2014) or the ability to extract and generate meaningful information from the supply chain data (Sahay & Ranjan, 2008). Employing these techniques enables organisations to explore the high volumes of available data, allowing for better decision-making and control of the supply chain.

The work presented in this dissertation addresses the problem of supply management, more specifically early deliveries monitoring, faced by Bosch Braga. Early deliveries cause significant problems to the company, such as the increase of stock levels, which possibly compromises warehouse occupation management. At the same time, this leads to an increase in purchasing costs. Currently, the company is unable to detect these delivery deviations, which makes it difficult to take actions quickly that mitigate the impact or prevent it from happening in the future. Despite having large amounts of data available that might potentially assist in this task, the company lacks a solution and a process. To tackle this, a BI&A is proposed and developed, allowing easy monitoring of supplier deliveries and detection of potential deviations. An analysis process is also created to support users in analysing the information and assist in decision-making. At the same time, there is a general lack of knowledge on potential causes and risk factors that lead to the occurrence of early deliveries. This is the case of Bosch Braga, but it is also seen in the literature, where there is a lack of knowledge about early deliveries. Therefore, a study is conducted into potential risk factors that affect suppliers performance and lead to the occurrence of early deliveries.

1.2 Objectives

The main objectives of this dissertation are to develop a data analytics and business intelligence solution that enables the company to detect and analyse supplier early deliveries, by identifying potential risk factors and develop a better understanding of the problem.

Keeping these objectives in mind, the following research questions (RQ) are proposed to be answered:

- **RQ1:** What is the current status of research and applications of BI&A in the field of supply chain management, more specifically, supply management?
- **RQ2:** Can BI&A help Bosch to detect supplier delivery deviations, improving visibility and reduce early deliveries?

- **RQ3:** Which factors appear to influence Bosch suppliers to send deliveries earlier than expected?

By answering these questions, the following sub-objectives will be achieved:

- Understand what the focus of academic work has been regarding the application of data analytics and business intelligence in the supply chain;
- Analyse and understand the material order and delivery processes of the company under study;
- Develop a solution that enables the detection and analysis of supplier delivery deviations;
- Develop a robust and clear analysis process to support the use of the solution;
- Improve the material delivery process, by preventing and reducing the occurrence of early deliveries;
- Identify potential risk factors leading to the occurrence of early deliveries.

1.3 Research Methodology

The research methodology chosen for this work was Action Research, due to its characteristics. This methodology is ideal for researches that focus on the resolution of organisational issues and is characterised by the involvement of organisation members in the research (Saunders, M., Lewis, P., & Thornhill, 2009). At the same time, the methodology is based on an iterative process of diagnostic, planning, action, and evaluation. Action research is recognised for its explicit focus on action and for promoting change within organisations (Saunders, M., Lewis, P., & Thornhill, 2009). Since this dissertation focus on a project carried out in a company, with a practical nature and aims at promoting change and improvement, action research was considered the most suitable methodology.

Saunders, Lewis and Thornhill (2009) state that action research starts within a specific context and with a clear purpose. This is followed by the four stages in the research process:

- **Diagnosis:** in this stage, the processes of the organisation are analysed and studied to understand the problem faced;
- **Action planning:** after understanding the problem, actions to address the identified issues are planned alongside organisation members;
- **Taking action:** actions are taken to address and attempt to solve the problems found;
- **Evaluating:** after actions have been put into practice and solutions implemented, the results are evaluated to access the impact on processes. This stage is the time for feedback to understand what has been improved and what is still to be improved.

After the end of the evaluation stage, a new cycle with all four stages initiates again. Here, the characteristic iteration of this methodology is evident. This iterative nature is important as it promotes continuous learning as actions are taken.

In action research, the researcher is involved by the organisation in the diagnostic phase. The following phases are owned by the researcher, with a great deal of involvement from the organisation. This form of action research involves the researcher in the organisation's issues. The researcher works as a consultant, with the organisation being the sponsor. The consultant's activities are known as "process consultation" (Saunders, M., Lewis, P., & Thornhill, 2009; Schein, 1999).

In this project, the researcher was responsible for the several stages of the methodology process and the actions, with the close involvement of members of the company throughout the entire project.

1.4 Dissertation Structure

This dissertation is organised into 5 chapters, structured as follows.

Chapter 1 presents the purpose of this work, the research methodology adopted, as well as the objectives of this work and the research questions it looks to answer.

In **Chapter 2**, a literature review is conducted on the topic of business intelligence and analytics in the context of supply chains. Previous works on this theme are explored to understand what the focus of past research has been and what applications have been studied. Research gaps and opportunities for future work are identified. It is also the goal of this research to gain awareness on the topic to transfer academic knowledge to business reality.

Chapter 3 starts with a brief presentation of the company, more specifically the Logistics department, where the project was carried out. Next, the material supply management processes are explained and critically analysed, and improvement opportunities are identified. The main problem is explained and formulated.

Chapter 4 presents the improvement proposals implemented to address the problem. The various actions developed that ended in the final BI&A solution are presented, as well as the results of the project.

Chapter 5 introduces a study developed to identify potential risk factors that lead to the occurrence of early deliveries. Potential risk factors are identified and historical data is collected. Data analysis is performed and conclusions and limitations of the study are presented.

The dissertation ends with **Chapter 6**, where the main contributions of this work are summarised, as well as the theoretical and managerial implications. Suggestions for future work and research on the topic are also presented.

2. Literature Review

As part of the project presented in this dissertation, a systematic literature review was carried out, which is presented in this chapter. The research process for this review is presented and explained, followed by a descriptive analysis of the results and a critical literature review. Research gaps and future research topics are identified.

This review aims to answer one research question:

- **(RQ 1):** What is the current status of research and applications of BI&A in the field of supply chain management, more specifically, supply management?

To better study and understand the work in this field, the research question was subdivided into the following research questions:

- **(RQ 1.1)** How does the literature define BI&A and how is it related to SCM?
- **(RQ 1.2)** What are the benefits, impacts and barriers in implementing BI&A in SCM?
- **(RQ 1.3)** To what problems has BI&A been applied in the field of supply management and, more generally, SCM?
- **(RQ 1.4)** What variables impacting or characterising supplier/delivery performance are identified in the literature?

Keeping this question in mind, the goal of this review is to understand what the focus of research regarding the use of BI&A in supply chain management has been, with a particular focus on supply management. We also aim at understanding the impact and benefits that BI&A has on this field and how it has been applied to solve supply chain problems.

2.1 Supplier early deliveries

Early deliveries, at first, might not seem a problem for companies. Normally, when thinking about delivery problems, people think about late deliveries which might cause supply chain disruptions. Indeed, late deliveries can more easily have significant impacts on operational performance. For instance, Parmar et al. (2010) only consider partial and late deliveries a problem, while Baryannis et al. (2019) classify early deliveries as successful deliveries like on-time deliveries. However, this does not mean that early deliveries are negligible and do not impact operations.

Early deliveries are not a studied topic in the literature. For this dissertation, preliminary research was carried out to understand what has been discussed regarding this topic, or even if there has been any. Indeed, and to the best of the author's knowledge, there has been virtually no research on early deliveries. Only Schneiderman (1996), Peng and Lu (2017), and Guiffrida and Nagi (2006) have addressed the topic, but no comprehensive study or analysis of the problem was made.

Despite this, some organisations are shifting to just-in-time manufacturing and processes and therefore are starting to pay attention to the topic (Schneiderman, 1996). Proof of that is Walmart, which has started fining its suppliers for delivering too early as well as too late (Bloomberg, 2017; Boyle, 2017; McKevitt, 2017; MH&L Staff, 2017; Pandolph, 2017) to improve their stock levels and operations. The impact early deliveries have on organisations depends on certain industry contexts (Peng & Lu, 2017). Yet, reducing early deliveries is desirable as they contribute to an increase in inventory holding costs (Guiffrida & Nagi, 2006; Peng & Lu, 2017).

As mentioned before, literature has not yet studied this topic in-depth, which is corroborated by Peng & Lu (2017) and Schneiderman (1996). Considering there is very little research on early deliveries, the research was broadened to supply management as a whole, as will be discussed in the following section. With this dissertation and the problem analysis carried out, it is intended to contribute to the literature and knowledge generation.

2.2 Research process

The publications analysed and presented in this review are a result of a systematic literature review. Scopus was chosen as it is considered the largest abstract and citation database and recommended as a good source for supply chain topics research (Fahimnia et al., 2015). This review aims to understand how we can leverage data and analytics and use it to our advantage to make supply chains more efficient. It is intended to perceive how past works have merged these two themes.

Although the problem studied in this dissertation is in a subfield of supply chain management, the search was not restricted to it and was extended to the supply chain as a whole, despite having a bigger focus on supply management. This was decided as it is believed that it is important to have the whole picture to understand the focus of the application of BI&A on supply chains.

With this in mind, a research query was defined with two sets of keywords, as shown in Table 1. The first set contains keywords referring to the business topic under study, in this case, supply chain, as a whole, but also to supply management. The second set of keywords refers to different expressions, techniques or technologies whose applications are to be studied on the business topic at hand.

The keywords and other search terms used are as follows:

Table 1 - Keywords and proposed search terms

Research Query	("supply chain" OR "suppl* performance" OR "inbound logistics" OR "suppl* risk" OR "suppl* disruption" OR "suppl* evaluation" OR "suppl* deliver*" OR "deliver* monitoring" OR "suppl* uncertainty" OR "logistics uncertainty" OR "transport operations" OR "suppl* management") AND (analytics OR "data mining" OR "multivariate statistic*" OR "data-driven" OR "machine learning" OR "data science" OR "business Intelligence" OR "process mining")
Article type	Journals
Language	English
Results	1159

The search returned a set of 1159 articles. Further filtering criteria was considered to focus on relevant articles to the topic:

- Articles published in top quartile journals (Q1 and Q2) were included. Articles from quartile 3 (Q3) were analysed based on citations, relevance, and originality of the topic, and included based on performance on these criteria. Articles published in quartile 4 (Q4) journals were automatically excluded.
- Only articles that addressed directly the topic of BI&A on supply chains were included.

By reading and analysing the content of the abstract of the remaining articles, it was possible to assess the relevance of the articles to the topic under study in this dissertation. This resulted in a final set of 114 articles.

2.3 Understanding Supply Chain Analytics and Business Intelligence

Despite the growing interest in the topic, there are still different views regarding supply chain analytics and business intelligence. According to Wang et al. (2016), analytics involves the ability to gain insights from data by applying different techniques to help organisations make better decisions, and supply chain analytics (SCA) is the application of business analytics (BA) to logistics and supply chain. Souza (2014) presents a similar definition, stating that SCA “focuses on the use of information and analytical tools to make better decisions regarding material flows in the supply chain”. SCA is a combination of approaches, procedures and tools used to gain and analyse information (Trkman et al., 2010).

Analytics can be categorised into three types:

- Descriptive analytics answers questions such as what has happened, what is happening and why (Hahn & Packowski, 2015; Souza, 2014; Tiwari et al., 2018). It explores the current state of affairs and aims at identifying problems and opportunities within processes and functions (Wang et al., 2016). Visualization tools, reporting and descriptive statistics are some of the techniques used (Souza, 2014; Tiwari et al., 2018);
- Predictive analytics focuses on answering what will be happening in the future or is likely to happen and why it will happen (Hahn & Packowski, 2015). It attempts to predict the future state of affairs (Souza, 2014; Tiwari et al., 2018; Wang et al., 2016). It can be used, for example, to forecast customer demand and understand buying behaviour (Tiwari et al., 2018).
- Prescriptive analytics is the use of data and mathematical algorithms to determine what should be happening and how to influence it and to assess alternative decisions (Tiwari et al., 2018; Wang et al., 2016). It answers questions such as what should be done and why should it be done (Hahn & Packowski, 2015). Techniques used include simulation, mathematical optimisation and multi-criteria techniques (Souza, 2014; Tiwari et al., 2018; Wang et al., 2016).

Arunachalam et al. (2018) present the same definiton as Souza (2014). However, the authors go a bit further, defining Big Data Analytics (BDA) capabilities in the context of supply chain management as "the ability of organisations to collect and organise supply chain data from heterogeneous systems distributed across organisational boundaries, analyse it either batch-wise or real-time or near real-time and visualise it intuitively to create proactive supply chain system and support decision making". The authors also introduce the term Business Intelligence (BI).

BI can be defined as "the use of technology to collect and effectively use information to improve business potency" or as "a range of analytical software and solutions for gathering, consolidating, analysing and providing access to information that enables organisations to make better decisions" (Sahay & Ranjan, 2008). It can be used to manipulate data and generate information and business inputs, empowering companies to make decisions in a fast and reliable way. BI systems allow data reporting and analysis, complementing Enterprise Resource Planning (ERP) systems, which are complex, inflexible and difficult data analysis tasks (Chou et al., 2005).

Sahay and Ranjan (2008) state that are different views on BI, depending on who is defining the term. However, the authors argue that BI includes the extraction, transformation and loading (ETL) operations, data warehousing, database query and reporting, data analysis, data mining, dashboards and visualisation. The four components of BI systems are data sources, data warehouses, data marts and query and reporting tools (Sahay & Ranjan, 2008). The authors state that SCA is the ability to extract and generate meaningful information from data. It appears that, according to their view, BI is the system responsible for data gathering, storing, analysis and reporting, and is the key enabler of SCA. Putting it another way, BI enables the ability to extract information for decision-makers from the enormous amount of data that supply chains generate. They seem to suggest that SCA is a consequence, the objective, or the final state of implementing BI systems in supply chains, implying that SCA can be viewed as part of BI.

BI is a set of tools, applications and technologies, such as data warehousing, online analytical processing (OLAP), data mining dashboards, analytic and reporting tools, among others that enable information gathering, recording, recovery, manipulation and analysis and improve decision-making (Sangari & Razmi, 2015). BI is viewed as “an organized and systematic process of acquiring, integrating, analysing, and disseminating information from both internal and external sources that are significant for revealing strategic business dimensions and for decision-making purposes (Sangari & Razmi, 2015). BI consists of tools to support data-driven decisions, with a focus on extracting information and reporting, while BA comprises the use of statistical and mathematical skills, allied with IT abilities and business vision for decision-making (Barbosa et al., 2018). These definitions also suggest that BI has an analytical component and BA might be part of BI.

This idea is not strange in literature and is supported by several authors. BA has come to be seen as a key analytical component of BI (Barbosa et al., 2018; H. Chen et al., 2012). Gudfinnsson et al. (2015) also view BA as part of BI and use both terms interchangeably (Arunachalam et al., 2018). Chen et al. (2012) use the term Business Intelligence and Analytics (BI&A), and define it as “the techniques, technologies, systems, practices, methodologies, and applications that analyse critical business data to help an enterprise better understand its business and market and make timely business decisions” (Barbosa et al., 2018; Papadopoulos et al., 2017). Barbosa et al. (2018) argue that BI, BA and Big Data are often used in the same context and use BDA as a broader term that encompasses both BI and BA. BDA should be seen as a more general term that includes the analytical techniques applied to datasets so large that require advanced and unique data storage, management, analysis and visualisation tools (Barbosa et al., 2018; H. Chen et al., 2012).

Sangari and Razmi (2015) define supply chain BI competence as “the ability to provide the supply chain-related information and knowledge that supports supply chain decision making at different levels, ranging from strategic network planning, outsourcing, and procurement to detailed scheduling and lot-sizing”.

Chae and Olson (2013) view BA and BI similarly as they believe both reflect a need for developing and using analytical tools and capabilities for organisational and decision-making processes and they aim to find intelligence within large volumes of data. SCA is defined as “IT-enabled, analytical dynamic capabilities for improving supply chain processes” and its objective is to manage supply chains efficiently and effectively. The key capabilities of SCA are data management capability (data acquisition and transformation, analytical supply chain process capability (capability to analyse supply chain processes data), and supply chain performance management capability (capability to monitor processes and improve based on data analysis) (B. K. Chae & Olson, 2013). This supports the idea of BA and BI being similar.

It is noticeable that there is a lack of consensus regarding the definitions of BI and BA and their relation to SCM (Barbosa et al., 2018). Different terms are used by different authors. In this work, BA will be considered as part of BI, or as the analytical component of BI, and terms like Supply Chain Analytics (SCA), Supply Chain Analytics and Intelligence (SCA&I), or Business Intelligence and Analytics (BI&A) will be used interchangeably. Lastly, SCA&I is proposed to be defined as:

> *“The application of tools, techniques and technologies to gather, transform and analyse data, generating useful information to support and improve supply chain management”*.

2.4 Implementing SCA&I: benefits, impact, success factors, barriers and challenges

2.4.1 Impact and Benefits of SCA&I implementation

For organisations to adopt and invest in BI&A for their supply chains, there have to be advantages and benefits, that will lead to improvements in operations. BI&A becomes more important for organisations, as they realise that the information generated from data is critical for a successful supply chain (Sahay & Ranjan, 2008). SCA enables more responsive and agile supply chains, as it allows a better understanding of market trends and preferences. By getting to know better their supply chain, organisations will adopt a more proactive behaviour, as they will be able to anticipate events, risks and disruptions (Tiwari et al., 2018).

Keeping this in mind, several authors have carried out studies and surveys to understand the main benefits of adopting SCA and BI, but also to evaluate the impact that their adoption has on supply chains and organisations performance.

Schoenherr and Speier-Pero (2015) surveyed 531 SCM professionals, that pointed out several benefits in adopting data analytics, such as, more informed decision-making capabilities, ability to improve supply chain efficiencies, enhanced demand planning capabilities, improvement in supply chain costs, and increased visibility. For instance, predictive analytics is believed to lead to better demand forecasts and customer experience promotions, reduction in demand risk and information disruption risks, a better quality of contingency plan activation, and increased supply chain visibility (Ivanov et al., 2019). SCA can be of great help to managers and decision-makers, by supporting them in understanding changing marketing conditions, identifying and assessing supply chain risks, and formulating and implementing supply chain strategies, leading to improvements in flexibility and profitability (Wang et al., 2016). SCA and BI allow organisations to make better decisions and more proactive behaviour, by continuously monitoring their supply chain, thus detecting and anticipating events, risks, and disruptions (Sahay & Ranjan, 2008; Tiwari et al., 2018). These capabilities that SCA&I gives to organisations can lead to more agile supply chains and could be the success factors of supply chains in the future. SCA will provide a better understanding of market trends and preferences, leading to more responsive and agile supply chains. SCA increases SC managers' awareness of the external risks and events and will enhance the social, environmental and financial performance of SCs (Tiwari et al., 2018). Combining the ability to respond to disruption events with SCA has a positive impact on the ability to build SC risk resilience (N. P. Singh & Singh, 2019), meaning that companies will be able to prepare and react better to risk events.

Chae and Olson (2013) propose a framework to implement SCA and present several propositions to study the impact of BA on SC and argue that the greater the level of SCA, the greater the level of Supply Chain performance is. However, the authors underline, that SCA is composed of three capabilities:

1. Data Management Capability (DMC): the ability to collect, store and manage data and provide access to it;
2. Analytical Supply Chain Process Capability (APC): the ability to apply analytical techniques to supply chain processes;
3. Supply Chain Performance Management Capability (SPC): the ability to observe, monitor, decide and improve their supply chain processes.

The authors propose that the greater the level of each capability, the greater SC performance is. Nevertheless, it is stated that for SCA to work, the three capabilities are needed and rely on each other. For instance, organisations that have good data management capabilities and analytical capabilities, but do not have performance management capabilities, are unable to follow up on data insights and improve their supply chain. At the same time, if companies are unable to manage or analyse data (DMC and APC), they will not be able to identify what needs improving and follow up on that (SPC). Therefore, by aggregating these three capabilities, the level of SCA can be estimated and will have a positive impact on supply chain performance. At the same time, a final proposition is presented, stating that the higher the level of environmental turbulence, the higher the contribution of SCA to supply chain performance is.

One of the first studies using a large-scale field survey approach, with a sample of 161 US companies, showed that the use of BDA in the supply chain has a positive impact on both asset productivity and business growth (D. Q. Chen et al., 2015). However, this impact is moderated by environmental dynamism, meaning that organisations operating in highly changing markets will see a greater impact on their supply chains. This seems to support the proposition previously presented by Chae and Olson, (2013), that SCA has a higher impact on performance in firms operating in more turbulent environments. This can be explained as firms that operate in highly dynamic environments need to react quickly and take accurate decisions on time, as they need to anticipate clients' needs and uncertainties. Therefore, analytics plays a critical role in assisting in the decision-making process. This means that the market in which organisations operate and its customer demands, pulling for more agile and responsive supply chains, might be a trigger for the adoption of SCA. Technological factors have a direct influence on the use of analytics, while organisational readiness and competitive pressure have an indirect influence (D. Q. Chen et al., 2015), thus showing that the vision, strategy and skill when it comes to the use of technology influence the adoption of SCA.

A more recent study conducted by Wamba et al. (2020) provided support to the idea that SCA has a positive influence on SC agility, adaptability, and both cost and operational performance. However, the study presents contrary evidence to the idea supported by previous authors (B. K. Chae & Olson, 2013; D. Q. Chen et al., 2015), suggesting that the effects of SCA on SC agility adaptability and performance were higher in intermediate levels of environmental dynamism, but weak with low and high levels of environmental dynamism. One possible explanation for this conclusion might be that organisations operating in highly dynamic environments focus their attention on adapting their operations to the changing circumstances, and neglect BA. These mixed results reinforce the need for more studies into this idea, to form a better understanding of how environmental dynamism affects SC performance, indicating that this could be an interesting topic for future research.

Sangari and Razmi (2015) also found evidence that SC BI competence has positive effects on agile capabilities and agile performance of the SC.

Another study concluded that the impact of analytics on operational performance is not direct, but rather indirect, as it is contingent on the adoption of SCM programs, such as Total Quality Management (TQM), Just-in-time (JIT), and other SCM practices (B. Chae et al., 2014). This supports the idea that BA alone is not enough and does not lead to better performance but instead must be combined with efficient SCM practices and business domain knowledge that can originate improvements in supply chain processes and, consequently, performance. Keeping this in mind, organisations must develop their BA capabilities, but also their SCM and process improvement capabilities. These conclusions are backed and complemented by another study based on data collected from 537 manufacturing plants, that concludes that data management, IT-enabled analytical and planning, and performance management resources have a positive impact on supply chain planning quality and performance, which in turn has a positive impact on operational performance (B. K. Chae et al., 2014). However, the study showed that data management and IT-enabled analytical and planning resources have an indirect impact on SC performance through performance management resources. This evidence reinforces the idea that the technological components of SCA, despite being key to building successful SCA initiatives, are not enough if not complemented by the capability to improve processes and manage performance, through data-based driven practices. Data management and analysis provide the inputs that are necessary for successful supply chain performance management.

Another finding was that these resources, despite distinct, are related, exemplifying that the level of data management capability is a good indicator of the level of the other two resources (B. K. Chae et al., 2014). Such conclusion provides evidence that companies who have mature data management and analysis processes are more likely to have more mature SCM practices and processes. In turn, this leads to better SC performance.

Similar conclusions were presented by Srinivasan and Swink (2018), who showed that analytics has a stronger impact on operational performance when supply chains have more organisational flexibility to act on the insights provided, by improving costs and delivery performance. This once again shows that for analytics to have a greater impact on performance, firms need to act on the information generated-

It has also been shown that SCA capabilities can increase supply chain transparency and that sourcing is one of the areas where supply chain transparency would increase the most as a result of investment in analytics (Zhu et al., 2018).

Roßmann et al. (2018) conducted a Delphi study with SCM experts, where 16 projections of the future of BDA in SCM in 2035 were made and evaluated. The main conclusions were that BDA will be a key driver in improving supplier performance, demand planning and safety stocks. This will be a consequence of more accurate demand forecasts, leading to lower inventory levels, and supplier management will be improved by growing amounts of data that is available for analysis. SC operations will face less uncertainty and more SC transparency, as a result of BDA, will allow faster decision-making and responses to SC disruptions. On the opposite side, it is projected that decision-making processes will remain within the scope of SC managers instead of Artificial Intelligence (AI), autonomously machine-based supply negotiations are unlikely to be a reality, and supplier audits will not be replaced by BDA.

Despite the obvious focus that supply chain performance gets regarding the application of BI&A, other impacts have been studied and should continue to receive attention. Jeble et al. (2018) tested different hypotheses and concluded that analytics, combined with other organisational resources, has a positive relationship with the sustainable and social performance of organisations, which had been projected by Tiwari et al. (2018).

A study using data from 320 companies from all over the world, found support to the idea that the use of BA in SC processes impacts its performance, thus reinforcing the importance of using databases, explicative and predictive models and fact-based management to make decisions and take actions (Trkman et al., 2010). The results suggested that the adoption of good information systems is likely to improve the performance of analytical capabilities. However, the study also suggested that business process orientation does not have a strong moderating effect. This is contrary to other studies previously mentioned, that supported the idea that good process management was essential for the success of analytics and SC performance improvement. The authors point that this might be explained by the sample of the study, which might have included more process-mature companies, and that business process orientation of companies can increase as a side-effect of developing BA. The authors also point that companies that are more aware of the importance of BA and process improvement may be more likely to accept participating (Trkman et al., 2010). Finally, the study also showed that BA can have a bigger impact on different SC areas than others. Make is the area that would benefit the most, followed by Plan and Source. Again, this is contrary to the findings of Zhu et al. (2018), which suggest that sourcing is the area that could benefit the most with analytics.

These results show that more research is needed on the impact of SCA on organisations with different levels of maturity regarding process management as well as the impact across different areas of the supply chain (Plan, Source, Make and Deliver).

In a later study, Oliveira et al. (2012), demonstrated that investment in BA is beneficial for organisations at every level of maturity, however, BA's impact on SC performance depends on the level of maturity of organisations, as the impact is lower for lower levels of maturity. This once again appears to support the idea that business process development and management are important and BA's impact relies on that.

Oliveira et al. (2012) also found evidence that BA has a different impact across SC areas (Plan, Source, Make and Deliver) according to the level of process maturity. For instance, companies at the lowest level of maturity will benefit the most from BA in Plan and Source, as BA might help them evaluate and improve their processes. At this level, for example, Sourcing could benefit from the implementation of supplier evaluation and performance measurement systems, which could lead to more awareness of sourcing performance and consequently to improvements. At higher levels of maturity, Source is once again the area that would get the most benefits from the use of BA. At these levels, companies work closely with their suppliers in product development, collaboration and integration, supply network management strategies and outsourcing (Oliveira et al., 2012). This requires companies to monitor, evaluate and analyse their suppliers and sourcing processes to better know the performance of their supply chain and improve it. This study supports the idea that BA's impact is different across different areas of SC and in different companies, according to how mature they are in their processes, providing possible explanations as to why BA implementation might go wrong in some situations. At the same time, it provides some guidance about what should be the strategy and steps considered when implementing SCA.

Data-driven SCs have a significant positive effect on SC dimensions, such as information exchange, coordination with customers and suppliers, interfirm activity integration, and SC responsiveness, leading to new opportunities in SC transparency, visibility, and process automation, and improvements in SC financial performance (W. Yu et al., 2018). Data-driven SCs are also positively associated with different manufacturing capabilities like quality, delivery, flexibility, and cost, which in turn lead to increased customer satisfaction (Chavez et al., 2017).

Based on the works analysed, it is possible to understand that are significant impacts regarding the application of BI&A on SCM. These advantages can be translated into more agility and responsiveness, better operational and financial performance, and customer satisfaction, among others. Despite the research developed so far, more studies into the impact are needed (B. K. Chae & Olson, 2013), as there are still many topics regarding the impacts of SCA that have mixed findings, while others have not yet been explored. Some conclusions, gaps and topics for future research are listed:

- There is a lack of understanding regarding the impact that different types of analytics (descriptive, predictive and prescriptive) can have on SC performance. Therefore, more research on the topic is proposed;
- It would be important to study the impact of BI&A across different industries and types of organisations, to understand what factors influence each specific context and how they can take advantage of the use of BI&A. Here, environmental dynamism could play an important part, as mixed results were obtained regarding the role it presents on SCA's impact;
- More research on the impact of BI&A across different areas of SCM is needed to better understand where in SCM would BI&A prove itself more beneficial;
- Despite some studies about the impact of SCA on global indicators of SC performance, there is a lack of understanding about how can BI&A be the trigger and lead to improvements in more specific indicators, such as customer satisfaction, on-time delivery or supplier performance.

2.4.2 Success factors, barriers and challenges in implementing SCA&I

As previously observed, implementing BI&A in SCs can bring several benefits to organisations and lead to significant improvements in SC performance. The literature has addressed the benefits of SCA&I with relative frequency. However, there has not been much research into what challenges and barriers organisations and managers might face when implementing (Papadopoulos et al., 2017).

Earlier, by identifying some contingencies associated with the successful implementation of SCA and its impact on SC performance, it was possible to learn about what some success factors might be.

For the successful implementation of SCA, data management capabilities, analytical and IT capabilities, and SC process and performance improvement capabilities are crucial (B. K. Chae et al., 2014; B. K. Chae & Olson, 2013). Without any of these capabilities, SCA implementation might fail to deliver its results. Without good data management, data analysis becomes unreliable, and process improvement might be unfruitful. Without data analysis capabilities, it is not possible to generate insights for SC improvements. Lastly, without SC improvement capabilities, data management and data analysis become a waste, as no follow-up is done.

This idea finds support in the study developed by Oliveira and Handfield (2019), who found that analytics and decision making depends on 3 primary capabilities: statistical capabilities, deep business knowledge, and knowledge of information technology. To achieve these capabilities, organisations need, respectively, data scientists, supply chain experts, and IT experts. With a combination of this set of capabilities and skills, organisations will be able to leverage SCA and improve their supply chain performance. This idea is also mentioned by Barbosa et al. (2018), who points this presents a challenge for organisations, as it is difficult to find professionals with strong IT, statistical, and SC skills. Organisations must form multi-disciplinary teams. However, professionals from one background must have knowledge of the other two. For example, SC professionals need to have some background and knowledge on IT and statistics to know what technologies, tools and techniques are available. This will allow them to better identify supply chain problems and possible solutions that might lead to improvements. The ideal SC analyst has both SC understanding and analytical skills, as the effectiveness of analytics will be bigger if the analyst is deeply engaged with the topic (Waller & Fawcett, 2013).

Before developing analytical capabilities, managers should consider and evaluate several factors, like the ability of their supply chain to acquire timely and accurate information, their organisational abilities to be flexible and shift priorities, assets and resources, as well as the competitive value of sensing and responding to changing market conditions Srinivasan & Swink (2018). According to the authors, trying to develop analytical capabilities but failing to meet these conditions, is not likely to improve operational performance.

Arunachalam et al. (2018) divide the issues and challenges organisations face when adopting analytics into two categories: organisational and technical challenges. The former include time consumption, insufficient resources, data privacy and security concerns, behavioural issues, return on investment, and lack of skills. The latter comprise data scalability and storage problems, data quality, and lack of techniques and procedures.

Sanders (2016) states that four barriers prevent companies from taking advantage of data: first, the need to keep up with the hype, which results in using analytics randomly and unnecessarily; second, the selection of applications that optimise specific processes but fail to link across the supply chain; third, the excessive amount of metrics and difficulty to figure out what metrics to focus on; and fourth, the "paralysis", a state where many organisations find themselves with so much data, but not knowing what to do with it.

A survey conducted on 531 SCM professionals revealed that 28% of respondents were not familiar with analytics (Schoenherr & Speier-Pero, 2015). This might indicate that unawareness might also be one of the biggest challenges that SCA might face to assert itself in organisations. This shows that awareness of SCA needs to be raised by conducting more studies on its benefits, as well as through successful implementation cases in real supply chain problems. The primary barriers identified by the survey included employees' inexperience and need for training, time constraints, the cost of the available solutions, or change management issues. Lack of appropriate predictive analytics solutions for SCM, as well as the perception of SCM predictive analytics being overwhelming and difficult to manage, were also pointed out by the respondents as barriers. Once again, this supports the idea that awareness of SCA must be raised through more research, to overcome these barriers.

Another finding was that the group of respondents that plans to use analytics in the future perceived the lack of data and the inability to identify data most suitable for analytics, while the group that already uses analytics to a great extent (Schoenherr & Speier-Pero, 2015). This might show that more mature companies, that are already using analytics to a great extent, have already developed a capability to gather and store data, thus feeling this is not a challenge anymore. Indeed, data quality and management are essential for successful analytics, as data analytics is only as good as the data used (Hazen et al., 2014, 2018).

Data-related barriers, such as data quality and complexity of data integration, were also the major barriers identified in a study on 5 companies, followed by technology-related barriers (Moktadir et al., 2019). The other major sub-barriers indicated were the lack of infrastructural facilities, data privacy, high cost of investment, and lack of available analytics tools.

Indeed, data barriers might be one of the biggest challenges organisations face. Data tends to be scattered across multiple systems, software, databases and files, forcing companies to gather operational data from multiple sources, integrate and store it. Systems like ERPs are complex and not very flexible, making it difficult to extract, store and analyse the available data (Chou et al., 2005). Lack of integration with current systems is another barrier uncovered by Schoenherr and Speier-Pero (2015). This might require more IT infrastructures and, consequently, investment, which might put organisations off investing in SCA.

Nonetheless, organisations must realise that it is not possible to transform analytics functions overnight and it is a process that takes time and requires a strategic plan to set the way forward (Ivanov et al., 2019). Arunachalam et al. (2018) present four implications for best practices of analytics:

1. building a data infrastructure;
2. developing capabilities to integrate data and information sharing across the supply chain;

3. developing analytics, starting by developing basic analytics (descriptive) and moving incrementally towards more advanced analytics (predictive and prescriptive);
4. integration of analytics into business processes and acceptance by management of predictive analytics as a support tool to decision-making.

To successfully adopt and leverage SCA, companies must have a structured approach and strategy. With the barriers in mind, Sanders (2016) claims that the implementation of SCA should be an evolution, and provides some guidance, by presenting a maturity map composed of four stages:

1. Data digitisation and structuring, where data is digitised, structured and cleansed, ensuring data quality;
2. Data availability, where data is made available to everyone at every time;
3. Basis analytics, where basic analytics tools, descriptive analytics and correlation analysis are deployed;
4. Advanced analytics, where predictive and prescriptive analytics, real-time data analysis and automated algorithms are deployed.

Sanders (2016) mentions that it is a mistake for companies to try and jump stages and as they pass through the several stages they learn and continuously improve. Many companies tend to follow the trend of analytics, trying to develop more sophisticated algorithms and analytics without having the foundations to succeed. This provides support to the opposite idea. The author also mentions that many companies do not require advanced analytics, as basic analytics can provide powerful and meaningful insights.

Based on the revised works, it is clear to say that data-related issues are the most commonly reported. Indeed, data management and quality are key for successful SCA, as actions derived from analytics, will be based on the insights provided by that data. By logic, if the analysed data is of poor quality, the insights and subsequent actions will be of poor quality as well, and will not generate improvements for supply chains. Therefore, data quality and management should receive tremendous attention from organisations and SCA researchers. Other issues identified include the necessary investment to adopt SCA, the lack of personnel skills, or the lack of knowledge and awareness of SCA.

However, literature on SCA barriers is still scarce and, therefore, more studies and practical cases are needed to better understand and form a complete view of what is holding organisations back in the adoption of SCA. There is also a lack of research regarding barriers in different SC areas, such as supply management. Research on the topic is of extreme importance, as knowing the barriers and challenges faced will enable the development of solutions to overcome them. Consequently, this will raise awareness of the topic and advance the level of SCA adoption and research.

Keeping this in mind, the following gaps are identified and research topics proposed:

- Further studies into barriers to the adoption of SCA;
- Studying what type of barriers different industries and types of organisations face;
- Studying what barriers can be found across different SC areas (Plan, Source, Make and Deliver);
- Identification of barriers at different stages of analytics (for example, challenges when building data gathering and storing infrastructures) and different types of analytics (descriptive, predictive and prescriptive).

2.5 SCA&I in Supply Management

2.5.1 Overview

When it comes to the application of BI&A in SCM, it is noticeable that there is still a recent topic and little research has been carried out. However, supply management is possibly the less explored area in SCA&I applications.

Papadopoulos et al. (2017) point out that procurement was found to be the area where research is more limited. Other authors also conduct literature reviews that fail to identify any practical application of analytics in supply management problems or find a limited number of practical cases (Barbosa et al., 2018; Mishra et al., 2018; Tiwari et al., 2018). Chehbi-Gamoura et al. (2019) conducted a literature review and found that only 14% of research was focused on supply management applications, while merely 11% of the papers analysed by Nguyen et al. (2018) were focused on analytics in this topic.

Despite the apparent little research on BI&A in supply management problems, this is one of the areas that could benefit the most from its application (Oliveira et al., 2012; Zhu et al., 2018) as it could lead to increased process quality (Ivanov et al., 2019). Several authors point that analytics has numerous potential applications to supply management problems, such as supplier evaluation, price negotiation, and supply network mapping, on a more strategic level (B. K. Chae & Olson, 2013; D. Ni et al., 2020; Wang et al., 2016). On an operational level, SCA can be used to evaluate supplier performance, to reveal hidden information about processes through pattern recognition, to segment suppliers according to their characteristics, to predict and anticipate SC disruptions and identify sources of uncertainty, or to monitor the inbound supply chain and raw material transportation (Baryannis, Validi, et al., 2019; B. K. Chae & Olson, 2013; Hahn & Packowski, 2015; Sanders, 2016; Souza, 2014; Wang et al., 2016).

Handfield et al. (2019) presented an extremely comprehensive study of the current status of analytics in procurement. According to the study, spend analysis, price benchmarking, supplier performance, and risk alerts represent the top 4 procurement needs for better analytics. The authors state that while the impact of data analytics is widely recognised, detailed applications are still a not much-explored topic and are still in the development stage. Organisations are only beginning to explore the power of analytics, meaning that there still is a long way to go to reach a new age of procurement. Thus, the authors point that future research should study how analytics can serve specific functional needs.

Handfield et al. (2019) present a roadmap, detailing the current common practices, current best practices, and future best practices. An example that highlights the delay in this area is the common practice of using excel spreadsheets to store, clean, and analyse data, and to create reports. In the current best practice, data is pulled automatically from ERPs and databases and new analytical tools, visualisation software, and running pilots. The future best practices will include the application of technologies like Internet of Things (IoT), artificial intelligence, machine learning and real-time analytics. In the future, analytics enhanced by these technologies will create "new forms of agile business insights into supply management", taking procurement management to the next level (Handfield et al., 2019).

2.5.2 Applications

Supplier selection

One of the most explored supply management issues is supplier selection. Supplier selection is a critical strategic problem for supply chains, as choosing the right supplier is the first step to guaranteeing a smooth flow of material supplies. Supplier selection is one of the possible applications of analytics in supply management (D. Ni et al., 2020; Tiwari et al., 2018; Wang et al., 2016).

This is by far the most explored analytical problem in supply management in this review, a finding that is supported in the literature (B. K. Chae & Olson, 2013; Ha & Krishnan, 2008; Wang et al., 2016). Several methods have been used, especially Fuzzy methods Data Envelopment Analysis (DEA) and Analytic Hierarchic Process (AHP), among other multi-criteria and operational research methods (Ha & Krishnan, 2008; R. Jain et al., 2014; Vipul Jain et al., 2009; Souza, 2014; Tiwari et al., 2018; Wang et al., 2016). Machine learning methods have been less used, but have gained some attention and have the potential for use in this topic (D. Ni et al., 2020).

Grey set theory has been explored in the supplier selection problem. Grey system theory is a mathematical method used to study uncertainty in systems, which is particularly helpful when dealing with uncertainty, imprecise or incomplete data (G. D. Li et al., 2007). Grey relational analysis was combined with rough set theory and applied in different works (G. D. Li et al., 2007, 2008).

Fuzzy association rules mining can also help deal with uncertain information and was used to support the supplier selection decision-making by (V. Jain et al., 2007). Also, by checking the classification rules, decision-makers develop knowledge about the problem their suppliers' behaviour (V. Jain et al., 2007). Baykasoğlu and Gölcük (2019) present an approach that combines fuzzy cognitive maps and times series with a metaheuristic method and generates short, medium and long-term matrices, allowing decision-makers to evaluate supplier performance over different time horizons (past, present, and future).

As mentioned before, AHP and other multi-criteria decision methods are widely used (R. Jain et al., 2014; Souza, 2014). However, methods such as the AHP are uncertain and unreliable, as they depend on experts' opinions and views and are subjective (R. Jain et al., 2014; Zhao & Yu, 2011).

To tackle this issue, different authors have attempted to combine these methods with more fact-based approaches, such as statistical and machine learning approaches, creating hybrid approaches. Ha & Krishnan (2008) propose a hybrid approach that uses the AHP method to assess qualitative criteria and DEA and neural networks on quantitive data. The outputs of both are then combined, leading to a combined supplier score. Hosseini and Khaled (2019) also attempted to tackle the AHP problems by combining the method with logistic regression, decision trees and neural networks, which are used to analyse historical supplier data. Ijadi Maghsoodi et al. (2018) applied multi-criteria decision-making supported by supplier cluster analysis. Cheng et al. (2017) presented a hybrid model combining DEA and the adaptative boosting method. Wu (2009) uses DEA to classify suppliers as efficient or inefficient and then employs decision trees and Neural Networks to predict new suppliers' performance. Geng and Liu (2015) use data mining to determine supplier selection criteria weight, followed by multi-criteria decision-making. A similar approach is presented by Golpîra (2018), allowing inputs from the decision-makers regarding their risk aversion, which is important as different managers might have different views on cost and performance trade-offs. These approaches have the advantage that criteria weight are fact-based instead of opinion-based.

Zhou (2016) also combined data mining techniques with multi-criteria decision methods for the green supplier selection problem. Liou et al. (2019) deployed a random forest algorithm to explore the relations between several attributes and suppliers' environmental performance and determine attributes weights for a multi-criteria decision model.

Other research works have paid more attention to the application of statistical and machine learning techniques. These methods have the advantage to be entirely data-driven. However, data gathering and quality may rise as a potential issue. Petroni and Braglia (2000) use principal component analysis in the supplier evaluation and selection problem. The advantage of the method compared to the previous ones is that is completely data-driven with no inputs from experts and the importance of each supplier attribute and performance are calculated objectively. M. Ni et al. (2007) has combined quality function deployment (QFD) with data mining to link customer requirements and products' performance with supplier patterns, thus getting a view of suppliers' performance. Lin et al. (2009) propose an association rules mining approach to identify critical parts and then create supplier sets and clusters for those parts.

Cheng et al. (2020), in an attempt to tackle the limitations of their previous work (Cheng et al., 2017), used support vector regression to develop an intelligent supplier selection model to reduce the inputs and need for experts in the selection process. To combat the subjectivity and inaccuracy of traditional models, Zhao and Yu (2011) use k-means and k-modes clustering algorithms to discover similarities between suppliers, followed by a backpropagation neural network to automatically revise results and extract new rules. Cavalcante et al. (2019) combines the use of simulation and supervised machine learning and build a hybrid approach to select suppliers more likely to deliver orders on time. Zhang et al. (2016) develop a neural network trained by historical order data several that evaluates supplier features and how it affects performance, ranking suppliers accordingly.

Agility measurement

Agility is a widely and commonly used term in SCM. However, there is a lack of methods to evaluate and quantify SC agility. Vipul Jain et al. (2008) developed an approach based on fuzzy association rules mining that supports decision-makers in understanding how agile their supply chains are. Agility is evaluated based on criteria like flexibility, profitability, quality, innovativeness, proactivity, speed of response, cost and robustness. Despite not addressing this issue directly, Alexandra Brintrup et al. (2020) also present a method to calculate agility.

Sourcing strategy optimisation

Different optimisation problems in strategic sourcing are also studied in the literature. Chi et al. (2007) present a model that attempts to optimise replenishment parameters like shipping frequency, store visiting frequency, shipment trigger policy, order-up-to inventory levels, or delivery lead times, when facing demand, lead time and sales conversion rate uncertainties. Support vector machines were used to predict supply chain behaviour, followed by a genetic algorithm that optimises replenishment parameters, in a display of the combination of predictive and prescriptive analytics. Priore et al. (2019) applied machine learning to periodically review the best inventory replenishment policy. This tackles the problem fast-changing supply chains face, which is the need to constantly review their inventory policies, which is difficult to analyse due to the complexity and large volumes of data.

Lee and Chien (2014) proposed an optimisation model that seeks to allocate orders to the best suppliers, with the goals of maximising the performance of the selected vendors, diversifying and distribute risk, and minimise total cost. Piramuthu (2005) also sought to allocate orders to the best suppliers by employing machine learning techniques. Choy et al. (2007) combined online analytical processing, artificial neural networks and case-based reasoning to build a supplier knowledge system. This system suggested replenishment parameters, by integrating customer demand data, forecasting the required stock levels and allocating orders to appropriate suppliers, according to their performance and capacity.

Rengarajan Srinivasan et al. (2019) applied mean-variance analysis to climate change and weather data to measure risk in different regions for growing different foods and investigate whether companies should adapt their sourcing decisions.

Supply chain and supply monitoring

When it comes to SC and supply monitoring, literature is also scarce. Y. Li et al. (2010) presented a decision support system that enabled proactive control and early warning of food supply events. Based on historical data analysis, it was possible to predict and identify root causes of Death-On-Arrival of chickens in the food supply chain, generating early warnings that would allow the company to act proactively and prevent new events from happening.

Delen et al. (2011) presented a solution for blood supply chain monitoring that allowed managers control over stock levels and deliveries and KPI monitoring across the entire supply chain. This solution combined descriptive analytics, such as data visualisation, with optimisation (for inventory management), data mining and trend analysis. This led to improved supply chain visibility and, consequently, improved performance of a supply chain as critical as the blood supply chain, where shortages of inventory might cause human losses, and on the other hand, excess inventory might cause expirations and spoilage. This article proves that sometimes simple approaches, such as descriptive analytics, result in significant improvements. Delen et al. (2011) point that many times academic researchers try to develop complex analytics models, that have no business value and real-world applicability.

Park et al. (2016) developed and tested in a case a conceptual visual analytics framework that combines descriptive and predictive analytics. This interactive visual analytics system allows the view of the entire supply network and enables its monitoring and supports decision-making and supply network setting. Yesudas et al. (2014) proposed a BI solution for supply chain processes monitoring, such as inventories, order fulfilment or shipments. The dashboard gathers, cleans and analyses data, through correlation technique and descriptive analytics, presenting the most important variables and information for users' analysis. By providing operational intelligence, this solution presents insights to managers that enable them to make better decisions and improve their SC performance.

Meyer et al. (2018) presented and tested in different automotive industry companies a disruption management system capable of processing supply chain events and generate data to be processed and analysed in real-time. The authors combined knowledge management, real-time stream processing, data analytics, and mathematical optimization, creating a complete platform capable of monitoring supply chain activities. The system allowed companies to be fully aware of the status of their material deliveries, acting immediately when a disruption occurred. At the same time, the logistics service provider (LSP), can detect disruptions and immediately take actions together with the client to mitigate the impact, and consequently leading to increased customer satisfaction. This work also shows the importance of SC collaboration, in this case, between an LSP and its clients.

Based on the works analysed, it is possible to understand that SC monitoring solutions can lead to improvements in inbound operations, without the need for sophisticated analytics techniques.

Supplier performance and supply risk analysis

Supplier performance and risk analysis is an important process in supply management, as it enables the understanding of the risks, events, and characteristics affecting supplier and delivery performance. This task can be seen as complementary to supplier selection, despite differences, as the former has a more operational nature, while the latter is more strategic. Supplier selection is a strategic decision that attempts to choose the best supplier, while supplier performance and supply risk analysis aim to measure operational performance and find risks and variables affecting it, to improve it. Supplier performance and risk analysis results can serve as input to supplier selection.

Y. S. Chen et al. (2012) deployed data mining techniques to extract hidden knowledge from data to understand what criteria influence suppliers' performance. K-means clustering was used to divide suppliers into 3 clusters according to their performance in 3 dimensions (cost, quality and delivery, and communication). Then, decision trees are deployed to extract rules about supplier performance, generating knowledge about supplier performance. According to the results, flexibility, communication and price competitiveness are the biggest determinants of supplier performance. R. Jain et al. (2014) also made use of data mining techniques to evaluate what criteria influenced supplier performance and should be used for supplier selection. Parmar et al. (2010) point that supplier base management is an unsupervised learning problem. Supplier base management involves supply base rationalisation, supplier development and supplier evaluation. To achieve better supplier management, Parmar et al. (2010) apply clustering techniques and divide suppliers into 5 clusters according to their characteristics. By grouping suppliers according to their characteristics, a company has better information and can better manage its suppliers. This enables a more efficient resource allocation and allows organisations to identify problematic suppliers, focusing their improvement and development actions on them. Er Kara et al. (2020) proposed a data mining framework for supply chain risk management, which was tested on supplier risk management. The authors characterised suppliers according to their risk profile, by applying clustering techniques. Suppliers were allocated to 3 different clusters according to their risk profile. This allows the company to divide its suppliers into more manageable groups and identify risky suppliers and act accordingly to mitigate those risks.

Afify et al. (2007) develop an approach that combines statistical data pre-processing, clustering, and classification learning techniques to identify and characterize cyclical disturbances in a complex supply network. The authors explore different variables, such as shifts worked, total order and stock levels, to find correlations between them, identifying and characterising supply network disturbances.

B. K. Lee et al. (2016) develop a supply chain simulation based on a real business case and use the operational dataset to measure the level of risk. Then, a binary response model is employed to quantify the level of risk in the relationship between a supplier and a manufacturer. This enables the identification of bottleneck suppliers by comparing different risk levels, choose alternative suppliers in case of disruptions, as well as understanding what causes of risk, allowing for changes in operational settings and potentially supply improvement. Predictors like supplier storage capacity, production capacity, transportation capacity, reorder point, order level, reorder interval and lot size are used.

Sener et al. (2019) deploy a Bayesian belief network to identify the most important set of variables that affect supplier operational performance. According to them, supplier management is an ideal application area to benefit from the use of data mining tools to improve the decision-making process and, consequently, supplier performance. P. J. Wu and Chaipiyaphan (2019) use decision trees to understand the source of delivery vulnerability. By using logistics vulnerability data, companies can identify factors that affect their operations and how they interact with the system. The study points that accident region and accident rime are the two most important variables that affect logistics delivery vulnerability. Shipments in a certain region and at a certain time of the day were associated with the greatest frequency of high-severity accidents.

The use of data-driven solutions, such as these, allows organisations to make informed decisions, instead of subjective ones. SCA lets companies identify critical risk factors and extract rules from data, that allow them to better understand their suppliers and operations performance, and improve them, by acting on those risks and creating mitigation plans. Therefore, the investigation and adoption of intelligent and data-driven methods should be encouraged, as a way to better manage suppliers and supply networks, by understanding their behaviour.

Supply chain events prediction

Having the ability to predict what will happen in the future can lead take supply chains to a whole new level of efficiency and agility. If managers can anticipate SC events, like disruptions or other risk events, they will be able to act proactively and activate contingency and mitigation actions that will attenuate the effects or even stop those events before happening. However, this requires large volumes of data, as well as quality data, since bad data will lead to bad predictions (Hazen et al., 2014). At the same time, some of these predictive models are difficult to understand (black box models) might turn off SC managers (D. Ni et al., 2020).

Considering this, some authors have already explored the application of predictive techniques to supply chain events prediction. Several predictive models were tested by van der Spoel et al. (2017) to predict truck arrival time at a distribution centre, with the best performing model achieving a 72% accuracy rate within 2 hours of the actual arrival time. Estimating time arrival might be an important advantage for a company, as it allows them to anticipate possible disruptions and adjust their unloading and loading windows. This allows companies to be more agile and adapt their planning and, consequently, more efficient operations. Balster et al. (2020) also applied machine learning techniques to predict the estimated time of arrival (ETA) in an intermodal freight transport network. The problem was divided into subproblems that cover each leg of the network, with each leg having a machine learning model to predict the arrival of its transport. These predictions are then combined, giving a final overall ETA prediction that covers the entire transport chain. This approach allows carriers and companies to be fully aware of the status of their transports, predicting delays and allowing them to act accordingly, by taking measures in subsequent stages of transport and mitigating risks.

Brintrup et al. (2018) used a case study from the automotive industry to analyse interdependencies in the supply network. By employing naïve Bayes and logistic regression, the authors were able to predict hidden links in the supply network, which allows organisations to identify disruptions and how they will affect their entire supply network.

An integrated framework and approach of artificial intelligence and SC risk management are proposed by Baryannis et al. (2019). The authors attempt to predict supplier delivery delays using support vector machines (SVM), decision trees (DT) and decision trees with feature restrictions (RDT), to explore the trade-off between prediction performance and interpretability. If on the one hand, managers need accuracy to trust the model results, on the other they want to know the causes and understand what is leading to risk events occurring. The results showed that the more interpretable model (RDT) represented a sacrifice of 5% of recall (proportion of actual positives identified correctly), but a much higher compromise in terms of average precision, with a 37% decrease. This means SC managers must carefully define what they are willing to compromise: interpretability or prediction performance. Either way, to make this decision, it is key to define what problem is being addressed, as different problems require different models and different levels of interpretability and prediction performance.

Alexandra Brintrup et al. (2020) also proposed to use SCA to predict supplier disruptions in a real case study. First, data was processed and explored, followed by the definition of performance metrics, initial feature and algorithm selection. Lastly, feature engineering was carried out and new features were added to the model. Random forest was the chosen model, achieving good and promising performance results (precision of 83% and recall of 78%). The authors support the idea, presented by Baryannis et al. (2019), that supply disruption prediction faces a problem, which is data imbalance, as the number of successful deliveries tends to be much higher than the number of delayed ones.

2.5.3 Variables and factors used to analyse supplier and delivery performance/behaviour

When evaluating suppliers and delivery performance, several variables or criteria might be considered. This section presents some variables presented by different authors in their works, previously analysed. Variables and criteria will be divided into two groups: criteria used for supplier selection (more strategic level), and variables used to analyse supplier and delivery performance (more operational level). It is important to understand that many variables can be found being used in both sets of problems. With this, it is possible to understand what variables are being considered by the literature when assessing suppliers' performance, behaviour and risk. The goal is to have an overview of factors influencing supply performance and that should be considered/explored in this project. The identified variables can be consulted in Table 2.

Table 2 - Criteria and variables used in literature to analyse supplier and delivery performance/behaviour

Problem	Type of Criteria	Variables identified	References
Supplier Selection	Production and process management	Production facilities, Process/production capability, Development capabilities	Ha & Krishnan (2008), Zhang et al. (2016), D. Wu (2009), V. Jain et al. (2007), Petroni & Braglia (2000)
	Quality	Quality management, product quality, audits, quality systems	Ha & Krishnan (2008), G. D. Li et al. (2007), D. Wu (2009), Hosseini & Khaled, V. Jain et al. (2007) (2019), Zhang et al. (2016), Petroni & Braglia (2000), G. D. Li et al. (2008), Hosseini & Khaled (2019), Golpîra (2018)
	Claims and after-sales	Claims, Response to claims, After-sales services	Ha & Krishnan (2008), V. Jain et al. (2007), Ijadi Maghsoodi et al. (2018)
	Delivery performance	On-time delivery	Ha & Krishnan (2008), V. Jain et al. (2007), Petroni & Braglia (2000), G. D. Li et al. (2008), Golpîra (2018)
	Organisational strengths and management capabilities	Organizational control, Management of the firm, Cost reduction capability, financial conditions, Business plans	Ha & Krishnan (2008), D. Wu (2009), Zhang et al. (2016), V. Jain et al. (2007), Petroni & Braglia (2000)
	Communication and relationship	Customer communication, Response rate, Cooperation potential	Ha & Krishnan (2008), Hosseini & Khaled (2019), Zhang et al. (2016), V. Jain et al. (2007)
	Cycle time	Delivery time, Lead time, waiting time	G. D. Li et al. (2007), Hosseini & Khaled (2019), V. Jain et al. (2007), Hosseini & Khaled (2019), Ijadi Maghsoodi et al. (2018)
	Cost	Price, logistics costs	G. D. Li et al. (2007), Hosseini & Khaled (2019), V. Jain et al. (2007), Petroni & Braglia (2000), G. D. Li et al. (2008), Ijadi Maghsoodi et al. (2018), Golpîra (2018)
	Flexibility	Resilience, change flexibility, responsiveness	Hosseini & Khaled (2019), V. Jain et al. (2007), Ijadi Maghsoodi et al. (2018), Geng & Liu (2015)
	Origin	Facilities location, distance to destination	Zhang et al. (2016), V. Jain et al. (2007), Golpîra (2018)

Problem	Type of Criteria	Variables identified	References
	Data, information management and technological capabilities	Data administration, EDI capability	Ha & Krishnan (2008), V. Jain et al. (2007), Petroni & Braglia (2000)
Supplier/delivery performance analysis	Quality	Complaints, Overall quality, Quality system and improvements, Audits, Shipping quality	Y. S. Chen et al. (2012), R. Jain et al. (2014), Parmar et al. (2010), Er Kara et al. (2020)
	Orders	Number of orders, Total ordered quantity, Ordered quantity, Ordered material, Order date	Afify et al. (2007), Baryannis et al. (2019), Alexandra Brintrup et al. (2020)
	Delivery performance	On-time delivery, incoming accept rate, delivery date	Y. S. Chen et al. (2012), R. Jain et al. (2014), Parmar et al. (2010), Sener et al. (2019), Er Kara et al. (2020), Alexandra Brintrup et al. (2020)
	Supplier practices	Proactive cost reduction, R&D activities	Y. S. Chen et al. (2012), R. Jain et al. (2014), Sener et al. (2019)
	Communication	Communication	Y. S. Chen et al. (2012), Er Kara et al. (2020)
	Cost	Price competitiveness, order change and cancellation costs	Y. S. Chen et al. (2012), R. Jain et al. (2014)
	Flexibility	Compliance and flexibility, responsiveness, agility	Y. S. Chen et al. (2012), R. Jain et al. (2014), Er Kara et al. (2020), Alexandra Brintrup et al. (2020)
	Organisational strengths	Company size, Company age	R. Jain et al. (2014)
	Data, information and technology management	Data administration, demand forecasting	Parmar et al. (2010), Sener et al. (2019)
	Production	Shifts worked, Storage capacity, Production capacity	Afify et al. (2007), B. K. Lee et al. (2016), Sener et al. (2019), Er Kara et al. (2020)
	Inventory	Reorder point, Order level, Reorder interval and lot size, inventory police	B. K. Lee et al. (2016)

Problem	Type of Criteria	Variables identified	References
	Lead Time	Lead time, Lead time variability	Er Kara et al. (2020), Alexandra Brintrup et al. (2020)
	Origin	Distance to destination, location	van der Spoel et al. (2017), Alexandra Brintrup et al. (2020)
	Time horizon	Time of day/week/month/year, order date	van der Spoel et al. (2017), Baryannis et al. (2019), Alexandra Brintrup et al. (2020)
	Environmental factors	Congestion/ traffic flow, Weather, Traffic speed	van der Spoel et al. (2017)

It is possible to understand that many of these variables are subjective. This presents a problem, as different people might quantify them differently, which leads to different analyses. At the same time, some of the variables used are highly strategical and refer to suppliers' organisational characteristics and practices (such as investment in R&D, quality systems, production capacity) and are not easily available for companies. To get information about these variables, close collaboration with suppliers and openness is necessary, which is sometimes not the case.

On the other hand, it is possible to see that not many operational-related variables are identified, possibly because the use of analytics to assess operational performance, risk and to profile suppliers is lower when compared to strategical uses (like supplier selection). Several criteria are shared by the supplier selection problem and the supplier/delivery performance since these two problems are connected and overlap. Supplier selection problems attempt to optimise different criteria, like cost, quality, and performance to find the best supplier, while performance problems only seek to understand risk variables that impact and influence performance and operations. Supplier performance can be useful for supplier selection by providing variables to be taken into consideration when selecting and evaluating possible suppliers.

2.6 Other applications in SCM

By analysing the research results, it is possible to identify several applications of BI&A in different areas of SCM besides supply management. These publications were divided into four major themes: demand forecasting/customer management, warehouse management, transport and distribution, SC sustainability, and international location decision. Table 3 presents an overview of those works and the respective area of application.

Table 3 - BI&A applications in different SCM areas

Area of SCM	Problems	References
Demand forecasting and customer management	Sales Forecasting, Customer knowledge discovery, Customer sentiment analysis, Return management	Carbonneau et al. (2008), M. C. Chen and Wu (2005), Song and Kusiak (2009), A. Singh et al. (2018), Liao et al. (2008), Cui et al. (2018), Huber et al. (2017), C. C. Yu and Wang (2008), Lau et al. (2018), Kandananond (2012), Bala (2012), Murray et al. (2015), Altintas and Trick (2014), Murray et al. (2018), H. C. W. Lau et al. (2009)
Warehouse management	Order batching, Inventory clustering	M. C. Chen et al. (2005), Aqlan (2017)
SC sustainability	Sustainability risk assessment, Sustainability assessment, Analytics impact on Sustainability	Hazen et al. (2016), Mani et al. (2017), Abdella et al. (2020)
Transport and distribution	Distributor selection, Transport planning, Anticipatory shipping, Container flow prediction, Distribution planning	Zou et al. (2011), Bhattacharya et al. (2014), C. K. H. Lee (2017), Tsai and Huang (2017), Coyle et al. (2016)
International Location decision	Facility locations	Khalid and Herbert-Hansen (2018)

As it is possible to see, demand forecasting and customer management have more research when compared to other areas. Forecasting methods, customer knowledge discovery and sentiment analysis are some of the problems studied. Indeed, different authors and past reviews have confirmed that demand/customer management is the most explored research theme when it comes to the application of BI&A (Barbosa et al., 2018; Chehbi-Gamoura et al., 2019; D. Ni et al., 2020). This area has more studies than the other mentioned areas (warehouse management, SC sustainability, transport and distribution, and international location decision) combined.

2.7 Literature review summary and findings

Throughout this chapter, a systematic literature review was carried out to understand the research landscape of the use of BI&A in SCM. A research process was defined, research material was collected and, finally, the content of that material was analysed, presented and critically reviewed. In the beginning, the main research question **(RQ1)** was established:

> **(RQ1)** What is the current status of research and applications of BI&A in the field of supply chain management, more specifically, supply management?

This research question was divided into sub-questions, that have been answered throughout this review, and have allowed the understanding of the current status of research on the topic:

- **(RQ 1.1)** *How does the literature define BI&A and how is it related to SCM?* Regarding the definition of BI&A and its SC definition, several articles and views on the meanings of these terms were presented and analysed. A definition for SCA&I was proposed.
- **(RQ 1.2)** *What are the benefits, impacts and barriers in implementing BI&A in SCM?* Several studies and surveys on the benefits and impacts of SCA&I were analysed and their outcomes presented, allowing for a picture of the benefits identified in the literature. Simultaneously, barriers to the implementation of SCA&I were presented, as well as different strategies for its successful implementation.
- **(RQ 1.3)** *To what problems has BI&A been applied in the field of supply management and, more generally, SCM?* Given that this dissertation focuses on supply management, more focus was given to the applications of BI&A to different problems on this particular topic. Problems studied in the literature, as well as the solutions proposed, were presented and analysed, allowing the understanding of the current status of research on the topic. Other applications to different areas of SCM were also briefly addressed.
- **(RQ 1.4)** *What variables impacting and characterising supplier/delivery performance are identified in the literature?* By reviewing articles exploring different supply management problems (supplier selection, supplier performance, supply risk analysis, or delivery performance prediction), it was possible to identify different variables used to understand the delivery performance or to profile and discover knowledge on suppliers. These variables were grouped and presented.

By analysing past works and answering these questions, it was possible to gain insights on supply management, its problems, and the application of BI&A to them. With this, it is possible to identify different research gaps and opportunities for future work on the topic.

On the benefits, impact, barriers and success factors in implementing. Despite being possible to identify a lot of work on the topic, there are still some questions and ideas that require further research. Regardless of the different benefits and positive impacts of SCA&I identified, there is not much knowledge on how different types of analytics (descriptive, predictive and prescriptive) can benefit SC processes and performance. Also, it is important to study this impact across different industries and types of supply chains. At the same time, it is important to understand what benefits SC&I can bring to different areas of SCM and how it can impact different specific performance indicators (customer satisfaction, supplier/delivery performance, inventory levels, etc). Regarding the barriers, it is also important to study how they differ across multiple industries and supply chains. Lastly, it is of great importance to form a better understanding of barriers faced by organisations at different levels of implementing SC&A and developing analytics capabilities. By understanding these barriers better, it will be possible to propose customised strategies according to each organisation or supply chain's needs. By doing this, it is believed that awareness will be raised to the topic and the level of SCA&I adoption and research will increase.

On the applications of BI&A in SCM, more specifically, supply management. By analysing the work developed so far on the applications of BI&A in supply management, it was realised that research is still recent and scarce. This confirms what other authors had already found out and stated (Barbosa et al., 2018; Chehbi-Gamoura et al., 2019; Govindan et al., 2018; Mishra et al., 2018; Nguyen et al., 2018; Papadopoulos et al., 2017; Tiwari et al., 2018). This presents itself as an opportunity for research, as research is currently focused on other topics, more specifically, demand management (Barbosa et al., 2018). The most studied problem in supply management is supplier selection, accounting for almost half of the papers on supply management applications (20 out of 45). This topic is by far the most studied in the literature. The supplier selection problem, despite extremely important, is highly strategic. On the other hand, regarding more operational problems, there is clearly a gap. Problems such as delivery performance analysis and supplier knowledge discovery, and risk profiling still lack applications. However, operational inputs are critical for strategic problems. Without knowledge of SC operations, strategic decisions become inefficient. There is also a gap when it comes to supply operations monitoring. Having a full view of what is happening in its operations in real-time (or near real-time) is vital for the performance of supply chains. Therefore, more research on these problems and their solutions is needed. Another noticeable problem is that research is focused on more advanced solutions and models (predictive and prescriptive analytics) (D. Ni et al., 2020; Souza, 2014; Wang et al., 2016), building a gap between theory and practice, as many of these models lack applicability (Baryannis, Validi, et al., 2019). These models, despite having great potential, require large amounts of data, data quality and technical knowledge, that many organisations still lack. Following a structured strategy for the adoption and implementation of SCA&I is critical. Jumping stages and going straight for advanced analytics will compromise the success of SCA&I adoption (Arunachalam et al., 2018; Sanders, 2016). It is important to understand the problems faced and recognise the value BI&A can add to them (Wieland et al., 2016). Many problems and organisations do not require the most sophisticated and advanced solutions and significant improvements might be a result of simple but efficient solutions (Sanders, 2016). Therefore, there is a need to start exploring and researching simpler and more basic solutions (such as descriptive analytics and data visualisation solutions, which are the first step in building an analytics-driven culture) that will bring gains for supply chains and real-world problems. Failing to answer practical problems will likely lead to the non-adoption of these approaches or their unsuccessful implementation.

On the variables used to analyse/understand supplier and delivery performance/behaviour. After identifying and gathering the variables used to model/profile supplier and delivery performance, it is possible to understand that many opportunities rise here. Many of the variables used are highly strategic and subjective, which means they require some sort of expert assessment. If these assessments and evaluations are not done correctly, it might raise problems regarding their efficiency when approaching these problems. At the same time, many of the variables used to select suppliers or analyse their performance are supplier-related and are external variables, in the sense that they have to be provided by suppliers (for example, data administration, R&D investment, organisational control). It is possible to see that operations-related data, which tends to be more objective, is not used many times. This can be explained by the fact that most research has been focused on supplier selection, a strategic problem, where more strategic variables are used. Therefore, more research on operational performance, problems and solutions is needed to also form better knowledge of daily supply operations and what factors affect it. By knowing their operations and the sources of supply problems, organisations can act on them and consequently improve their SC performance.

To conclude, research on the topic is still recent and scarce and several gaps can be identified. However, this review shows that plenty of opportunities arise with it. The work developed in this dissertation aims to meet some of these gaps and contribute to the existing knowledge on the topic.

3. COMPANY OVERVIEW AND EARLY DELIVERIES PROBLEM ASSESSMENT

The present chapter provides an overview of the company where this dissertation was carried out. The material supply processes are presented to form a better understanding of the general problem and project. A detailed analysis of the current situation is carried out to understand the impact that early deliveries have on the company. Finally, the problem is exposed in detail and stated.

3.1 Company overview

3.1.1 Bosch Car Multimedia and Automotive Electronics

Bosch is a multinational company with subsidiaries and regional companies in over 60 countries, with over 400 000 associates worldwide and sales and service partners in roughly 150 countries and regions. Bosch Group operates in four different business sectors: Mobility Solutions (BBM), Industrial Technology (BBI), Consumer Goods (BBG) and Energy and Building Technology (BBE). In the business year of 2019, Bosch had a total sales revenue of 77.9 billion €. The BBM sector alone represents 47 billion €, around 60% of the total sales volume. Each above-mentioned business sector comprises different functions: cross-functions; divisions; subsidiaries; and/or business units (Bosch, 2020).

Bosch Car Multimedia (CM) is one of the divisions of the BBM sector. With its intelligent solutions, Bosch CM contributes to making the integration of in-car entertainment, navigation, telematics and driver-assistance systems more flexible and efficient, while keeping it as easy as possible to operate. CM develops hardware and software of the present and actively shapes the future of connected mobility.

During the time this dissertation was under development, the Car Multimedia division was undergoing a merger with the Automotive Electronics division (AE), whose portfolio focuses on semiconductors, sensors and control units (Bosch, 2020).

Bosch CM and AE have locations worldwide, which can be consulted in Figure 1.

Figure 1 - Bosch CM and AE plants (Bosch, 2020)

3.1.2 Bosch Braga (BrgP)

Bosch Car Multimedia Braga is the biggest plant in the CM division and the biggest Bosch location in Portugal. In 2019, Bosch Portugal had sales of 1.6 billion € and employed 6250. Bosch Braga had 3559 associates and sales of 1.332 billion €, which represents around 83% of Bosch Portugal's total sales (Bosch, 2020). This information is detailed in Figure 2.

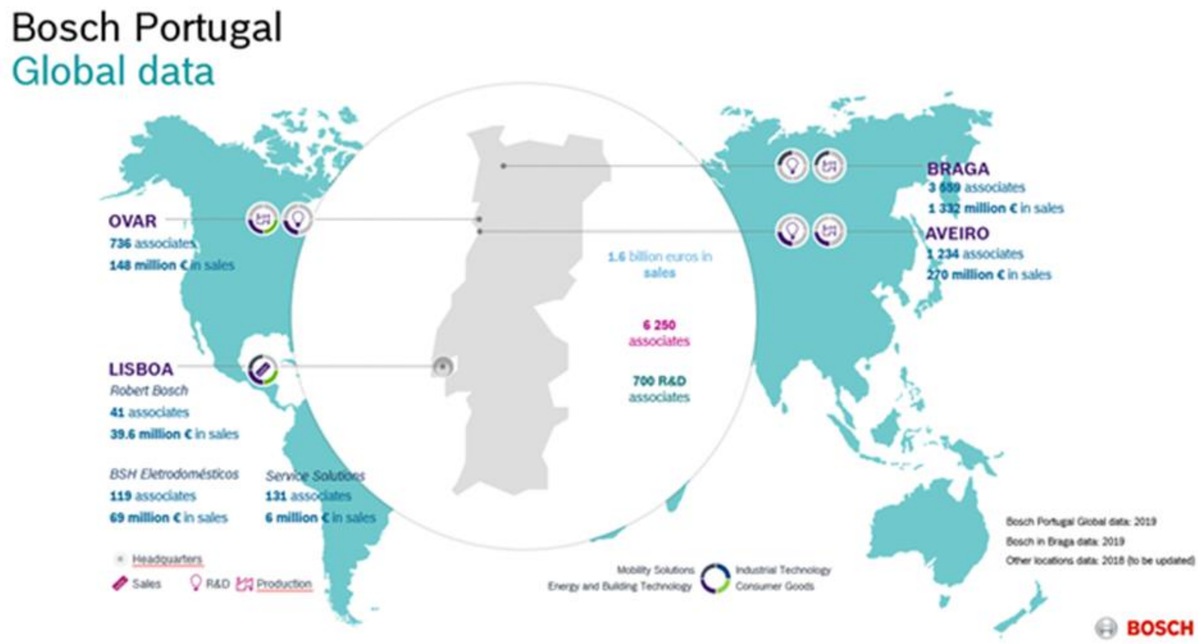


Figure 2 - Bosch in Portugal (Bosch, 2020)

Bosch Braga offers a wide range of products. Its portfolio has evolved from the traditional auto-radios for the automotive industry to a sophisticated product portfolio that includes navigation systems, infotainment systems, instrumentation systems, instrumentation clusters, steering angle sensors, or household electronics. Bosch's portfolio in Braga also offers services from a Research and Development Center, an Engineering Competence Center specialized in production, a Service and Repair Center, as well as an IT Service Center for Iberia.

With solid experience in the market, Bosch is recognised for being able to develop high-quality and flexible products. The proof of the quality Bosch Braga delivers is the wide range of high-level automotive brands that Bosch supplies, which throughout time have recognised the value and quality of Bosch Braga. Concerning the products manufactured, around 95% of them are to destinations in Europe and abroad. The company sells approximately 800 products to 181 customers worldwide. In what concerns the supply of raw material, Bosch Braga relies on more than 350 suppliers, both located in Europe and the Far East. Its purchasing strategy is based on a structure that encompasses three levels, such as National suppliers, European suppliers and Asian suppliers. The company works with around 8000 materials, or part numbers (PNs), and over 200000 inbound deliveries per year (Bosch, 2020).

3.1.3 Logistics at Bosch Braga

In general, Logistics ensures the availability of the right goods, in the right quantity, in the right quality, in the right place, at the right time, for the right customer, at the right cost.

Overall, Braga Plant (BgrP) Logistics (BrgP/LOG) is responsible for the coordination and improvement of the customer order processing, production planning, procurement, warehousing operations, internal logistics and shipping/billing activities, coordination and support the BrgP logistics projects. The vision of the department is to design and manage an agile logistics process for its customers. It is BrgP/LOG and its business partners' job to ensure a quick, stable and synchronised flow of information and materials throughout the supply chain. This way, BrgP/LOG can achieve the best-in-class delivery performance, quality and cost, while protecting resources and the environment. To ensure all this, BrgP/LOG is organised in the following sections, all of whom answer directly to the head of the department:

- **BrgP/LOC** – Logistics Controlling: This section links cost controlling with the various areas of Logistics. Some of their responsibilities are making forecasts of the evolution of logistics costs, cost monitoring, stock analysis, cost reporting and coordinating the process of debits to suppliers and customers;

- **BrgP/LOM** – Material flow and Internal Logistics: This section is responsible for the management of all the internal logistics flow and processes, such as productions lines supply, material receipt, product shipment, internal stock control, or warehouse management;
- **BrgP/LOP** – Customer Order Management and Production Planning: This section deals with customers daily, managing their orders and planning production accordingly;
- **BrgP/LOS** – Supplier Interface: This section is responsible for material supply and purchasing. They plan necessities and order materials according to the production plan, dealing daily with suppliers, to guarantee the availability of raw material. It is also their responsibility to monitor and track KPIs such as raw material stocks, supplier On-Time Delivery and transportation costs. LOS is divided into three teams: LOS2, responsible for electrical materials, LOS3, responsible for mechanical materials, and LOS, responsible for process management and support to LOS2 and LOS3.
- **BrgP/LOT** – Transport Management: This section is responsible for the transport organisation and management, freight control (import/export), organising urgent transports, and providing support for all shipments that require customs services (import/export from/to non-EU countries);
- **BrgP/LOI** – Logistics Innovation, IT Systems and Processes and Logistics Quality: This section is responsible for managing and developing projects for all the Logistics Sections, as well as process improvement. They also manage and support the department on IT systems, develop applications and automated reports, and are responsible for process quality, namely supplier and customer claims. Here is included the support on the Enterprise Resource System (ERP) used by the company, which is Systems Applications and Products in Data Processing (SAP). ERP software includes programs for all core business areas, such as supply chain, procurement, production, materials management, sales, marketing, finance, and human resources;
- **BrgP/LOD** – Packaging Design and Management: This section is responsible for the design of returnable packaging and its management and planning.

3.2 Material supply processes overview

The material supply process starts with the order release from Bosch to its suppliers. Bosch runs its Material Requirements Planning system (MRP) every Sunday. Based on the production plan needs, the MRP generates the orders with the required materials and quantities. After this step, the orders are released to suppliers, who should analyse them immediately and report any discrepancies or deviations in their delivery plan from the order schedule. The order management process overview is represented in Figure 3.

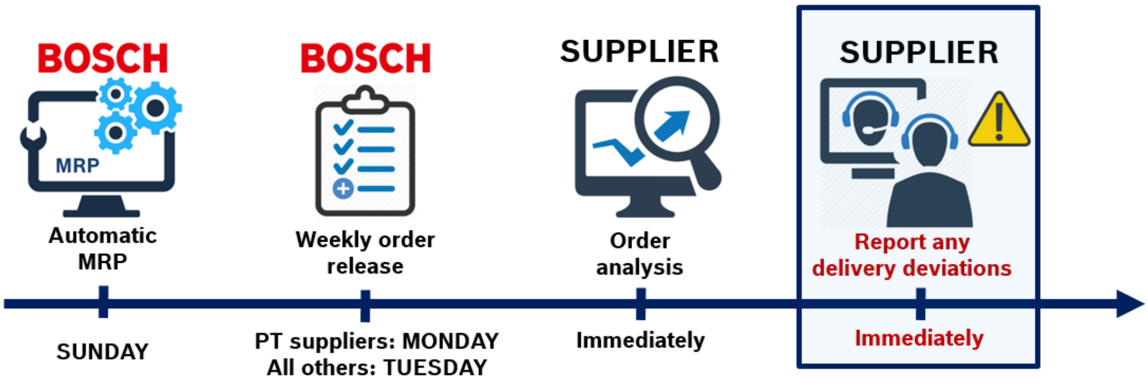


Figure 3 - Order management process overview (Bosch, 2020)

After receiving Bosch's orders, and if no discrepancies are identified, the supplier must ship the quantities requested at the correct dates. On the day the goods are shipped, the supplier must create the Advanced Shipping Notice (ASN). This electronic document contains all the relevant information regarding the delivery, such as, what materials are being shipped, in what quantities and the arrival date at the Bosch plant.

Next, a more detailed description of the order management and delivery processes will be provided to form a better understanding of some important concepts addressed and mentioned throughout the dissertation.

3.2.1 Order management process

MRP and orders release

As previously seen in the process overview, supply management starts with the MRP run every Sunday, which generates material orders based on production necessities and forecasts. Next, weekly order releases are sent to suppliers. Each material and its supplier are associated with a different schedule agreement (SA), also known as purchasing document. For example, a supplier with 3 materials, has 3 different SAs and receives 3 order releases weekly, one for each material. At the same time, if a material has 3 different suppliers, it has 3 different schedule agreements, one for each supplier. An example of an order release can be seen in Figure 4.

Shipdate	Deliverydate	Scheduled qty.(old)	Change	Delivered qty.	Open qty.
25.11.2019	04.12.2019	900	0	0	900
29.11.2019	09.12.2019	288	+360	0	648
02.12.2019	11.12.2019	576	+72	0	648
04.12.2019	16.12.2019	864	0	0	864
06.12.2019	03.01.2020	576	0	0	576
11.12.2019	06.01.2020	864	0	0	864
16.12.2019	08.01.2020	864	0	0	864
03.01.2020	13.01.2020	468	0	0	468
07.01.2020	15.01.2020	1.440	0	0	1.440
10.01.2020	20.01.2020	864	0	0	864
14.01.2020	22.01.2020	1.152	0	0	1.152
17.01.2020	27.01.2020	864	0	0	864

Figure 4 - Example of an order release (Bosch, 2020)

As seen in Figure 4, the order release contains the ship or pick up date, or Estimated Time of Departure (ETD), which is the date the goods should leave the supplier's facilities, the delivery date or Estimated Time of Arrival (ETA), which is the arrival date at Braga, as well as information regarding the quantities to be delivered and changes compared to the previous releases.

Incoterms

Incoterms are a set of rules and terms for the trade and sale of goods. They guide organisations participating in import and export activities and global trade daily (International Chamber of Commerce, 2020). Incoterms determine who has the responsibility for the transportation of goods, customs clearance, among other activities.

As a general rule, Bosch uses two incoterms: Free Carrier (FCA) and Delivery at Place (DAP). The main difference between these two in operations is the transport responsibility. In FCA, Bosch is responsible for picking the materials from the supplier, and transport them. Bosch hires an external transport carrier to ensure the transport of materials. By the time this dissertation was being developed, Bosch worked with one carrier, but a new carrier would start providing the transportation service, in parallel with the current carrier. This means that FCA suppliers must fulfil orders by delivering them to Bosch's carrier on the ship date indicated on the SA releases. In DAP, the supplier is responsible for delivering the goods in Braga and has to deliver orders at the Braga plant on the delivery date indicated in order releases. The differences between these two incoterms can be seen in Figure 5.

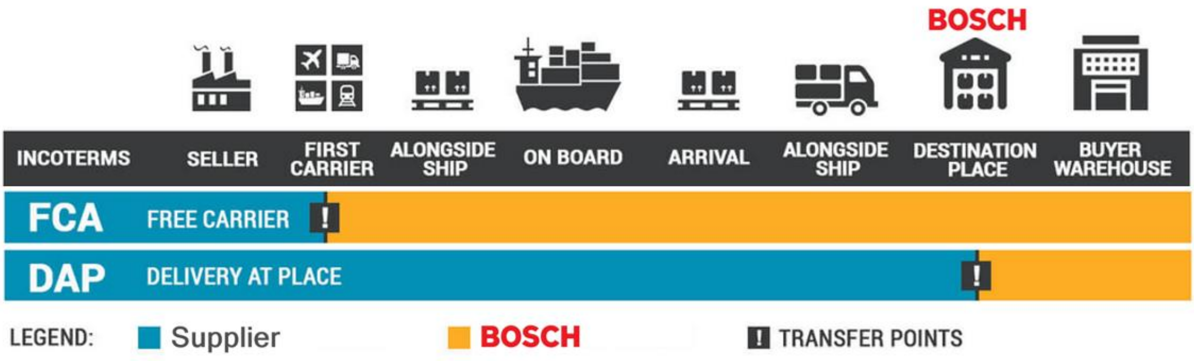


Figure 5 - Incoterms FCA and DAP (Bosch, 2020)

Planning time fence, production release and material release

Considering that MRP runs weekly and order releases are updated and sent, suppliers are constantly seeing their orders changed. To ensure that suppliers have some flexibility, plan their production and deliver materials efficiently, some order concepts are implemented.

The Planning Time Fence (PTF), or frozen zone, is the time horizon where the automatic MRP does not change its orders to suppliers. The PTF includes the time to process and prepare Bosch orders (generally, one week, except for national suppliers, where the rule is one day) plus the transit time of materials. During this time, materials are already supposed or about to be in transit. Therefore, orders cannot be changed by Bosch, unless agreed with the suppliers.

A production release (also known as production liability or firm zone) is also given to suppliers. This period is a time horizon where Bosch gives the go-ahead to suppliers to start production of the indicated material quantities. In case Bosch cancels the orders within the production release, the company must receive the produced quantities or pay the supplier its costs. However, during this period, Bosch can still change order dates. If an order lies within the production release, the supplier has the go-ahead to produce the quantities with the insurance that Bosch will bear any and all material and production costs associated with the ordered quantity in the event of a cancellation.

Bosch also gives its suppliers a material release (also known as material liability or trade-off zone) period. The material release works similarly to the production release. However, it refers to suppliers' raw materials needs to satisfy Bosch's requests. It is the go-ahead for suppliers to purchase the materials needed to satisfy Bosch's material orders. In case of cancelling the orders within this time horizon, Bosch must reimburse the materials' purchase costs to suppliers. If an order lies within the material release, the supplier has the go-ahead to purchase any input materials necessary to produce the scheduled quantities. Bosch will reimburse the supplier in full for any costs (but not for production costs) in the event of order cancellation.

These concepts are illustrated in Figure 6.

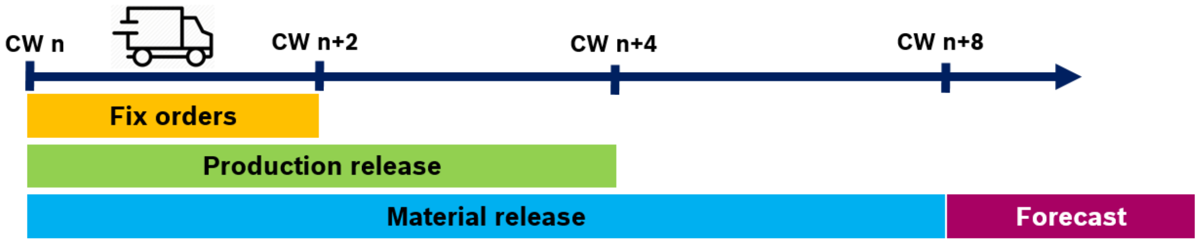


Figure 6 - Planning Time Fence, Production Release and Material Release concepts (Bosch, 2020)

Considering the content of Figure 6, a simple example can be formulated. In Figure 6, "Fix Orders" refers to the PTF. If Bosch has an order for a certain material of 500 units to arrive between CW n and CW n+2, this order cannot be changed, as it is inside the PTF and therefore, that quantity should already be in transit. If Bosch has placed an order of 100 units to arrive between CW n+2 and CW n+4, the company has authorised the supplier to produce those quantities and is committed to buying them. However, Bosch can still change the delivery date of those quantities. The company can postpone the delivery of those quantities for CW n+5 or CW n+8, for example. In the event Bosch cancels those orders, the company is liable for those ordered quantities and has to receive them. Bosch can reject the quantities but pay their cost. Facing a situation like this, the supplier must always check with Bosch how the company wishes to proceed.

Considering orders, between CW n+4 and CW n+8, these orders can also be changed and postponed or even anticipated. The quantities in that frame can be seen as an authorisation or a go-ahead for suppliers to purchase the necessary raw materials to produce those quantities. However, Bosch is not committed to those delivery dates. In the event Bosch cancels those orders, the company is liable for the supplier's raw materials and has to pay for them. Any orders beyond this period are forecasts and are subject to cancellation without any costs associated with it.

To sum up, the orders inside the PTF (fixed orders) must not be changed by Bosch, unless aligned with the supplier. On the other hand, orders inside the production release can be changed, but the company is already committed to buying those quantities somewhere in the future and is liable for them in case of order cancellation.

3.2.2 Material delivery processes

As previously addressed, as soon as suppliers receive the order releases, they must analyse the new orders and check them for accuracy, plausibility, and completeness, notifying Bosch in case any discrepancies are identified. If no communications are made by the supplier, Bosch will assume deliveries will be sent according to the latest release. Then, the supplier must prepare the deliveries according to orders sent by Bosch.

Suppliers operating under the FCA incoterm must book with the carrier hired by Bosch the weekly pick-up/delivery of the materials at the agreed location, for example, the supplier's factory/warehouse or a port nearby. These suppliers must deliver the materials to the carrier at the pickup date indicated on the release, the ETD. From there, the carrier transports the goods to the Bosch plant, and they should arrive on the delivery date indicated in the order release, the ETA. The transport time is the difference between the ETA and ETD.

On the other hand, suppliers under DAP incoterm deliver directly at Braga and choose the transport they see as the best fit. The materials should be delivered on the ETA indicated in the order release.

Under both incoterms, suppliers must create the ASN when the materials are put into transport. For FCA suppliers, this is the moment they deliver the materials to the carriers, which is the ETD. For DAP suppliers, who are not given an ETD on order releases, they must create the ASN at the actual time of departure of the delivery from their facilities.

The ASN is an electronic document that contains information about the delivery, such as the materials in the delivery, their quantities and the arrival date ate Braga. Creating this document is mandatory, as it is vital for Bosch to successfully monitor their upstream supply chain and be fully aware of the status of its material deliveries.

Finally, after exiting suppliers' facilities, the materials will be transported and delivered. However, the inbound process flow depends on the origin of the suppliers, as well as the transport mode. As can be seen in Figure 7, suppliers have different inbound processes depending on their origin. National suppliers supply Bosch daily, with a milk run that leaves Braga and picks up the goods in every supplier, and delivers them at Bosch Braga. The milk run runs six times a day. On the other hand, Asian suppliers mainly supply Bosch by sea transport, which delivers at Sines port. From there, it is transported by train to Leixões, and from there, to the external warehouse hired by Bosch. The materials are stored there, and then the external warehouse delivers them when needed. This transport of materials between the external warehouse and Bosch Braga is done several times a day. To have a picture of the dimension of these inbound operations, Bosch Braga works with around 500 suppliers, 8000 materials, or PNs, and has more than 20000 inbound deliveries.

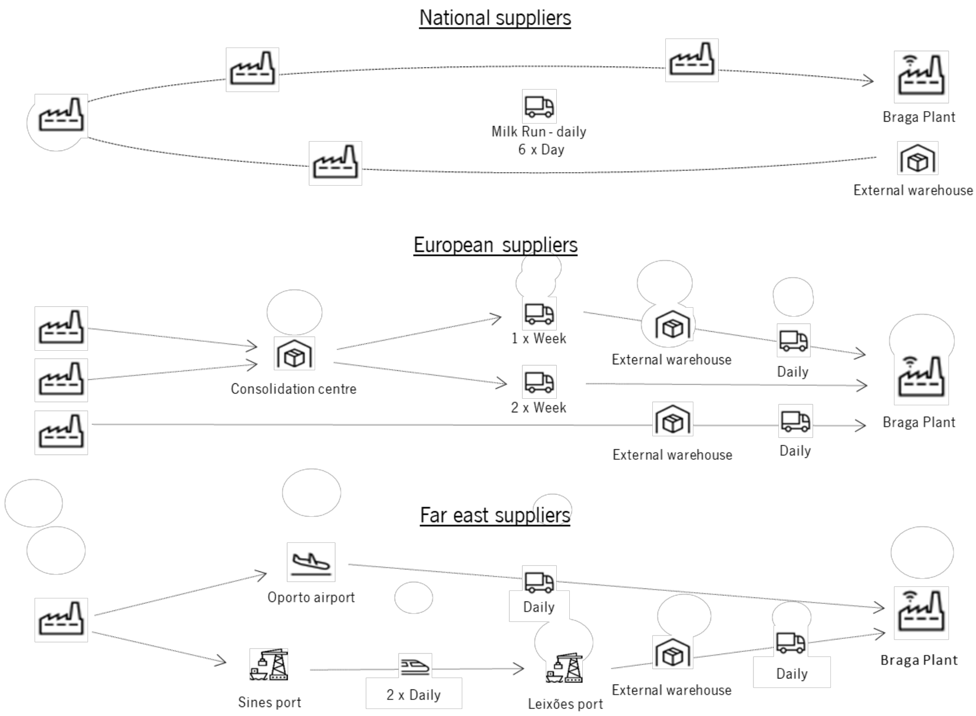


Figure 7 - Delivery process overview (Bosch, 2020)

3.3 Understanding the problem of early deliveries and its consequences

3.3.1 Understanding what an early delivery is

Early deliveries, or deliveries in advance, occur when a supplier sends a delivery that arrives at the buyer company earlier than expected. Early deliveries can occur in three different delivery situations:

- Delivery time too early: in this situation, the supplier delivers the amount ordered but fails to meet deliver it on the right date. For example, if a company has an open order for the 15th of June for 500 parts, but the supplier delivers those 500 parts on the 1st of June, it faces an early delivery where the delivery quantity was right, but the supplier delivered too early;
- Overdelivery: in this situation, the supplier makes delivers on the right day, but delivers more than ordered by the buyer. For example, if a company has an open order for the 15th of June for 500 parts, but the supplier delivers 800 parts on that same date, it faces an overdelivery, where the delivery date was correct, but the supplier failed to meet the ordered quantity and delivered more than expected;
- Delivery time too early and overdelivery: this occurs when the supplier fails to meet both the delivery date and ordered quantity. For example, if a company has an open order for the 15th

of June for 500 parts, but the supplier delivers 800 parts on the 1st of June, the supplier fails to deliver on the right date and also delivers more than expected.

At Bosch, these situations occur frequently, and many times suppliers fail to meet both the right delivery dates and quantities. When early deliveries arrive at Braga, they cannot be processed in the system, as deliveries require an open order in SAP to be processed. Therefore, early deliveries are registered in an excel file as pending materials until a date with an open order in the system. The materials are unloaded and stored in the warehouse. However, officially, they are still not in the warehouse, since the information is not in SAP. The materials will be processed in the system when the planner responsible for that material notifies the warehouse there is an open order available. On the 2nd semester of 2019, an average of 10,4 pallets arrived at the external warehouse every day, while on the 1st semester of 2010 this value was 10 pallets.

3.3.2 Impact and consequences of early deliveries

Early deliveries, at first, might not seem a problem for companies. Normally, when thinking about delivery problems, people think about late deliveries which might cause supply chain disruptions. Indeed, late deliveries can more easily have significant impacts on operational performance. However, early deliveries can have an impact on a company's operations and finances.

To get a better understanding of early deliveries, a detailed analysis is done to quantify its impact. The data analysed are the records of early deliveries registered between July 2019 and June 2020 on the external warehouse. This data is registered on an excel file. Only the external warehouse was considered for the analysis for different reasons. Firstly, the external warehouse faced the most critical situation in terms of available capacity and amount of early deliveries. Mostly mechanical parts from Asian suppliers, who only deliver once a week are sent to this warehouse. Since they are only sent once a week, they tend to send more quantities since their deliveries cover more days of supply, while National and European suppliers have bigger delivery frequencies, sometimes daily, delivering smaller volumes each time. At the same time, early deliveries in Braga are registered in a separate file, which was having technical problems and access to the file was not possible by the time this analysis was carried out.

The impact and consequences of early deliveries are identified, to form a better understanding of how critical this problem can potentially be for Bosch's operations:

- **Insurance and risk issues**: the first problem concerns the insurance and risk of storing those materials. Materials that are delivered earlier than expected can not be processed in SAP, since there needs to be an open order on arrival for that registration to be made. Therefore, the materials are registered in an excel file as pending materials. If the materials are not registered in the ERP system, they are not officially in Bosch's ownership and, therefore, are not insured in case anything happens to them. Also, the supplier cannot be held responsible for them, since they have already been delivered to Bosch. This situation raises potential risk issues in case any incidents occur (for example, a fire in the warehouse or thefts), as the materials are not insured and Bosch would have to assume the costs of the materials and lose the investment.

- **Materials' shelf life**: another issue that may arise with early deliveries is the shelf life that some materials have. If a material is sent earlier than expected, its shelf life will be shorter and there is an increased risk for the company. If the material is not consumed before its shelf life expires, it has either to be scrapped or to go through a lab process to extend its shelf life, with the costs to be borne by Bosch. This adds to the cost of the purchase of the material that is not used, resulting in waste and loss of capital investment.
- **Capital costs and financial liquidity problems**: early deliveries represent a large investment in material stock. Minimising inventory is crucial for organisations to reduce their investment in stocks and capital costs. Supplier early deliveries mean the company is investing more money than needed in stocks, and earlier than needed, which can result in liquidity problems. The value of early deliveries in the past can be seen in Figure 8.

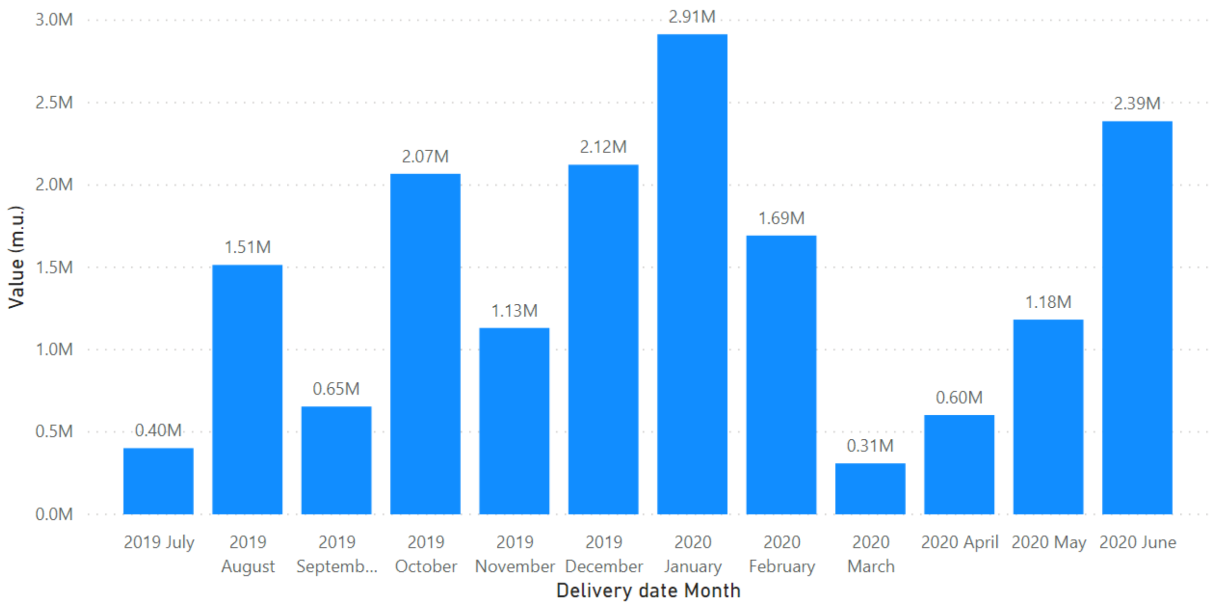


Figure 8 - Value of early deliveries (m.u.) at the LSP from July 2019 to June 2020

As it is possible to see in Figure 8, early deliveries delivered at the external warehouse represent a significant investment in materials. Considering these materials were not needed when they were delivered, it is an unnecessary cost that can potentially impact the company's finances and affect other necessary investments. In the second semester of 2019, the average value of early deliveries per month was 1,32 million monetary units (m.u.). In the first semester of 2020, the average value of early deliveries per month was 1,51 million m.u., an increase of around 1 million m.u. in six months. Adding to these costs, the company is also paying the carrier for the transportation of unnecessary materials from the supplier to its facilities, meaning there are more costs not quantified here.

- **Warehousing costs:** other costs the company faces are warehousing costs. Bosch has to pay the Logistics Service Provider (LSP), who runs the external warehouse, a daily fee for each pallet and box of materials stored there, as well as a fee for handling the materials. Table 4 shows the total warehousing costs (storage and handling costs) of early deliveries paid by Bosch in the second semester of 2019 and the first semester of 2020.

Table 4 – Early deliveries warehousing costs in the 2nd semester of 2019 and 1st semester of 2020

	Total Warehousing Costs (m.u.)
2nd semester 2019	16 251,09 m.u.
1st semester 2020	16 137,97 m.u.

- **Warehouse occupation and operational difficulties:** besides the operational costs associated, early deliveries also present operational problems to the company. Storing early deliveries leads to unnecessary warehouse occupation, which might compromise needed warehousing operations. Early deliveries also mean more handling operations, once again consuming time and resources that should be spared on necessary activities. As can be seen in Figure 9, the number of pallets and boxes of materials delivered earlier than ordered is significantly high.

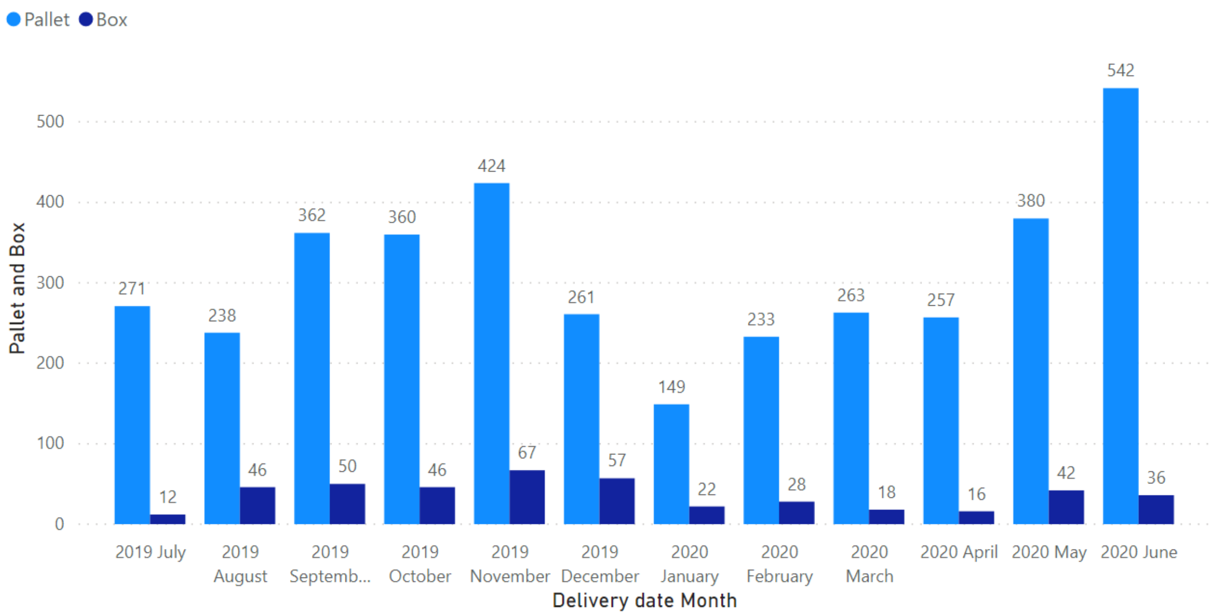


Figure 9 - Number of pallets and boxes delivered earlier than ordered at the LSP

To form a better understanding of the number of pallets and their impact on the daily operations, it is important to analyse some data regarding the daily operations. In the 2nd semester of 2019, materials delivered earlier stayed as pending materials on average 11,21 days before being processed in the system, while on the 1st semester of 2020 this value was 15,36 days. Considering the daily average number of pallets delivered earlier than ordered and the average number of days these deliveries materials are stored as pending material, it is possible to calculate the daily average number of pallets stored in the warehouse as pending materials. Considering the average stock of pending materials and the warehouse capacity (5347 pallets), we can calculate the average warehouse occupation in both periods (2nd semester of 2019 and 1st semester of 2020). This information can be checked in Table 5.

Table 5 - Impact of early deliveries on warehouse operations and occupation

	Total number of pallets delivered earlier	Average number of pallets delivered earlier / day	Average days stored as pending material	Average pallets of pending materials stored	Average warehouse occupation rate with early deliveries
2nd semester 2019 (184 days)	1916 pallets	10,4 pallets	11,21 days	117 pallets	2,2%
1st semester 2020 (182 days)	1824 pallets	10 pallets	15,36 days	154 pallets	2,9%

As seen in Table 5, early deliveries result in pending material that occupies significant storage capacity in the LSP's warehouse. In the second semester of 2019, the average occupation of the warehouse with pending materials was 2,2%, increasing to 2,9% in the first semester of 2020. Despite not appearing a lot, an occupation of almost 3% of the warehouse with unnecessary materials can have significant impacts on operations, especially considering sometimes the warehouse is being used close to its full capacity. This leads to reduced flexibility to deal with variations in demand of raw materials and operational difficulties. During July 2020, there were significant operational difficulties due to the high number of early deliveries. Some materials could not even be stored on the warehouse racks and were stored on the unloading docks and the floor, creating operational difficulties and unnecessary risks.

As it is possible to conclude, early deliveries can significantly impact Bosch's operations and financial performance, increasing the potential risks and operational difficulties. Therefore, it is important to address this issue and understand the problems behind it, intending to develop solutions that help Bosch act and deal with it.

3.3.3 Problem statement

After analysing the current status and consequences of the early deliveries problem, it was necessary to identify the problems and situations that are preventing the company to act on these early deliveries. Alongside the project team, with a procurement team leader, procurement section manager and one process expert as permanent members, several problems and situations were identified that required actions and solutions. Many of these problems are related to each other and are a consequence of a previous problem.

Problem 1 - Inability to block early deliveries. The first problem identified is the inability of the company to stop early deliveries from exiting suppliers' premises and preventing suppliers from sending unnecessary goods. With DAP suppliers, this was not possible, since they are responsible for the transport to Bosch's facilities and can transport the goods without any kind of blocking from Bosch being possible. However, when it comes to FCA suppliers, Bosch is responsible for picking up the goods at the supplier's premises. Despite this, early deliveries occurred with FCA suppliers. This happened since the carrier contracted by Bosch for the transport did not do any kind of verification when picking up the goods. The supplier could book any transport with the carrier and send any materials in any quantities as he would see fit. Without any kind of check when receiving the booking of pickups by the supplier, Bosch is failing to block early deliveries before they occur.

Problem 2 - Inability to detect early deliveries as soon as materials start transport. Another problem identified was the fact that Bosch was unable to detect early deliveries as soon they happened, i.e., when the materials start being transported. Bosch only notices an early delivery has occurred when it arrives at Braga and the warehouse reception team notifies LOS of a delivery without any open orders and registers the material on the early deliveries' excel file. This occurs since Bosch has no visibility over the goods in transit that are being sent by suppliers. This lack of visibility over their inbound supply chain prevented Bosch from detecting these delivery deviations in a more timely manner, which would allow the company to take quick actions to notify suppliers and act to mitigate the impact of these early deliveries. Instead of having full visibility into their inbound operations and detect these problems, Bosch was getting surprised with the arrival of unordered materials and quantities or wrong delivery dates.

Problem 3 - Inability to analyse early deliveries and detect the responsibility of the deviation. Bosch is getting early deliveries and detecting them when they arrived at its facilities. However, the company cannot detect the cause of an early delivery, and ultimately decide who is responsible for the early delivery (Bosch or the supplier), as there was a lack of an analysis process that would enable the investigation of the responsibility.

Problem 4 - Inability to take follow up and prevention actions on early deliveries. This problem is a direct consequence of the previous one. Since Bosch is unable to detect the cause/reason for each early delivery, the company does take any actions. When a supplier makes an early delivery, a complaint should be issued to the supplier. However, Bosch can not identify the cause of an early delivery to decide whether it was an internal (LOS responsibility) or external (supplier’s responsibility) cause. Without being sure whether the supplier should be held responsible for the delivery deviation, the company would not pursue any penalty and/or improvement with the supplier.

Problem 5 - Lack of knowledge on the early deliveries’ performance risk factors and identification of critical materials/suppliers. Lastly, another problem identified is the lack of knowledge on what are the variables and risk factors that might make a certain material or supplier prone to delivering earlier than ordered. That is, Bosch cannot understand the characteristics of the suppliers and materials with early deliveries. By having the ability to detect patterns and trends in early deliveries performance, Bosch can be aware of what factors might be correlated and explain a possible cause. Without this information, the company cannot build a profile of the errant supplier and identify critical suppliers and materials that should be given particular attention and monitoring. Building on a knowledge base, the company can investigate the problem further, and deploy development programs to improve suppliers’ performance. Simultaneously, this topic has not been studied in the literature. Therefore, this work presents an opportunity to gain some knowledge on the topic.

Building on the identified problems, actions and solutions were started to being conceived, studied, developed and implemented. The main goal was to create sustainable, practical and implementable solutions and processes that would allow Bosch to act and reduce the occurrence of early deliveries.

4. ENABLING THE DETECTION OF DELIVERY DEVIATIONS THROUGH A SCA&I SOLUTION

The present chapter presents the improvement actions studied and solutions implemented to tackle the early deliveries problem. Different actions were studied and taken throughout the project. Every action is presented one by one, breaking them down into the problem they attempt to address, its development and implementation and its outcomes. Finally, the results of the project are presented. This chapter presents 4 actions/solutions that address the first four problems. Problem number 5 is studied in Chapter 5. Figure 10 presents an overview of the different actions carried out and the problems they address.

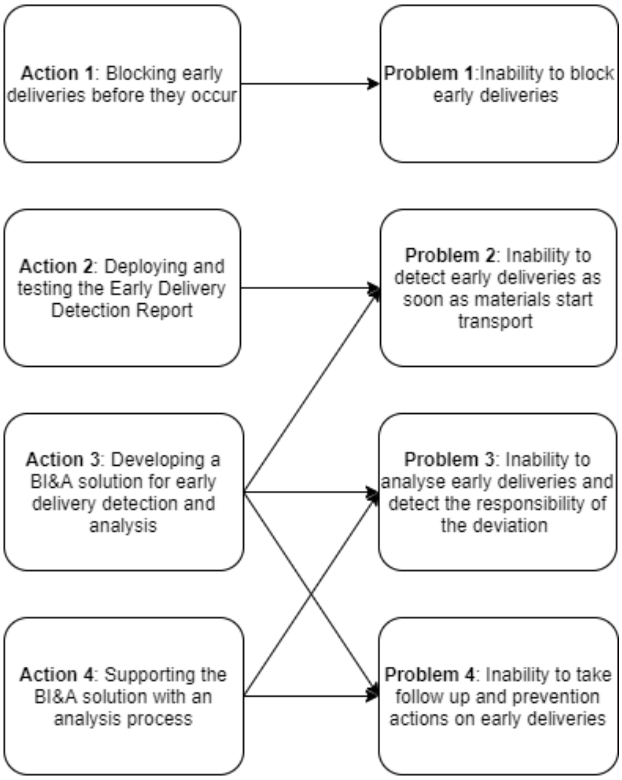


Figure 10 - Overview of the actions carried out and the problems they address

4.1 Blocking early deliveries before they occur

As mentioned earlier, one of the problems faced by the company was the inability to block early deliveries before they leave suppliers' premises (problem 1). With, FCA suppliers, a carrier contracted by Bosch is responsible for the pick-up of the materials and their delivery at Braga. However, currently, no verification is done by the carrier when receiving the booking of transport by the supplier or when picking up the goods. This means that suppliers can book with the carrier any quantities they wish to deliver without any vetting from Bosch.

Verifying the suppliers' transport booking would allow Bosch to check if there are any deviations in the quantities the suppliers are going to deliver, allowing the company to block those deliveries if they are not in conformity with the orders. Being able to stop early deliveries in the origin was considered a priority since it would significantly reduce early deliveries. Therefore, attempting to solve this problem was the first action.

4.1.1 Exploring the possibility of a picking list

To stop suppliers from sending early deliveries, it was necessary to create a mechanism to verify the quantities booked by suppliers with the carrier. This could be done if the carrier could access Bosch's open orders and compare them with the quantities booked by the supplier. The conceived idea would be a picking list with the quantities the carrier should load for transport or a solution that detected deviations between the open orders and the quantities booked by the supplier. A solution like this would require the collaboration of the carrier, as they would have to do the quantities check before or when picking up the goods from the supplier. Therefore, the solution would have to be developed together with the carrier.

Keeping this in mind, a meeting was held with the LOT team, responsible for the management of transport operations for Bosch Braga and for liaising with the carriers. The goal was to discuss a solution such as the one described before and understand its viability, the implementation strategy and the possible obstacles to be found.

In the meeting, several issues that compromised the solution were raised by LOT:

- Firstly, the contract signed with the carrier does not include the service requested, i.e., the verification of the quantities to be picked up at the supplier. Doing this service would require more resources and capacity on the carrier's side, which in turn could mean extra costs not stipulated in the contract. This would not necessarily be a problem, since the investment could have its return on the money saved with the early deliveries that would be prevented. However, the contracts with carriers were not negotiated by Bosch Braga, but by a central team. This central team is responsible for contracting the transports for all the Bosch division's operations. In the past, when the contract was made, Bosch Braga had already requested this requirement to be included in the contract. However, the request was rejected and not included in the contract.
- The LOT team stated that despite the first obstacle, the carrier could be approached by Bosch Braga to see if they were willing to implement the solution, but another obstacle was found. Even if the current carrier agreed to developing and implementing the solution, there was no

guarantee the carrier would remain the same in the next contract review. That is, if in the future a new carrier was contracted and this requirement was not to be included in the contract, the solution would have to be negotiated again by Bosch Braga, without any guarantees that it would be accepted. This meant that time and resources could be being wasted on a solution that was not sustainable and lasting in the medium and long term. Also, the LOT team pointed out that in a few weeks, a new carrier would start providing the transportation service, in parallel with the current carrier. This meant that two carriers would be providing the transportation service, which meant that the solution would have to be negotiated with two companies. In the event one of the companies refused to collaborate and the other accepted, the solution would not be implemented in the entire supply network, but only with part of it, creating inconsistencies and differences in supply processes. Once again, since this service was not negotiated, it could not be demanded of the carriers.

- Another difficulty presented by the LOT team was the fact that a verification of the booked supplier deliveries with the open orders could be time-consuming for the carrier due to the high volume of materials the carriers have to transport. Creating this step in the transport process could potentially increase the transport time of the materials up to 1 week. It is important to consider that a large proportion of FCA suppliers are based in Asia, with the transport being made by sea and taking around 2 months. An increase in the transport times could have a significant impact on the operations, since the Planning Time Fence would increase, giving Bosch less flexibility to change their orders and respond to material demand fluctuations.

Considering these barriers, and given the risk of going for a solution that had no guarantee of success in the medium and long term, and even in the short term, it was decided to not move forward with this proposal. The success of this solution was highly dependent on collaboration with the carriers. The solution would also need resources from the carriers, which were not negotiated when the contract was signed.

However, and in an attempt to plan for the future, the LOT team agreed to once again bring up this subject with the central team in the next contract review. Also, LOT agreed to make contacts with other Bosch plants to check if any of them struggle with this topic and would find beneficial the inclusion of this service in the contract with carriers since if more plants ask for this requirement, its necessity will gain strength.

One thing this case proves is the necessity of strategical and operational collaboration with supply chain partners, such as carriers, to successfully manage operations.

4.1.2 Lessons learned and conclusion

Despite the barriers that compromised this action go-ahead, this action could bring some benefits to the company, as it could prevent delivery deviations by stoping suppliers from sending materials and quantities that were not ordered.

In the future, Bosch Braga should discuss with the central team and other plants to highlight the problems Braga faces by not having carriers checking the deliveries they pick up from suppliers. For this solution to succeed, internal coordination is critical and contracts with carriers should include operational requirements from the business units. Therefore, plants need to be included in this contracting process.

Adding to this involvement of the business units, collaboration with carriers is key to successful solutions. Transport companies and other LSPs have to be seen as critical players in the supply chain that can influence, improve and guarantee the success of the company's operations. Therefore, it is important to look at LSPs as partners and part of the organisation, and not simply as mere external companies responsible for transporting the goods from point A to point B. Other services should be provided that nowadays are critical in transport operations. Such services include checking the deliveries being picked up for accuracy, blocking or notifying Bosch of any deviations, but can also include others such as delivery tracking and monitoring. Collaboration with carriers is important since they can provide and increase visibility over the inbound supply chain.

4.2 A BI&A solution to detect supplier delivery deviations: deploying and testing the Early Delivery Detection Report

After excluding the possibility of creating a loading list, a second solution to address the problem of early deliveries started being discussed. As previously mentioned, Bosch currently lacks visibility over its supplier deliveries. Bosch is not capable of detecting early deliveries since no comparison is made between the quantities in transit and the open orders released to suppliers. The company would only notice an early delivery had occurred when consulting the early deliveries excel file or when notified by the warehouse team. Some early deliveries would even go unnoticed and generally, no follow-up was done on them. This lack of information regarding the quantities in transit vs the open orders prevented the company from detecting early deliveries as soon as materials started transport. Consequently, by not detecting the deviations early, Bosch failed to react to them, by starting talks and reprimanding them, and possibly preventing more early deliveries from happening in the future (problems 3 and 4).

Considering this, the three problems previously presented in section 3.3.3 (problems 2, 3 and 4) can be grouped since they are intrinsically connected. This is because to successfully address each problem, the other two also need to be tackled. Problem 2 is analytical since Bosch did not make use of existent data to detect deviations in supplier deliveries. Problem 3 is an analytical and process problem since the company lacked the analytical tools and a structured process to analyse data and study possible causes. Finally. problem 4 is also a process and performance management problem since the company was not taking any follow-up actions. This occurred as a direct consequence of the two previous problems.

As seen, these three problems are dependent on each other. Without an analytical capability to detect early deliveries, it is not possible to search for possible causes and act, since deviations are not visible. Analytical capability, by itself, is not enough, since if no follow-up is made on the data insights, they prove themselves worthless.

Considering this, it is important to develop a solution based on an analytical capability and a process and performance management capability.

The first step in developing a solution is to define what are the objectives of the solution and the functionalities it must have, i.e., what must the solution be able to do and provide to the users. Keeping this in mind, together with the team, the functionalities and objectives of the solution are defined:

- The solution must allow the detection of materials with early deliveries while they are in transit;
- The solution must quantify the early delivery (in quantity and value) and allow the prioritisation of the most critical materials;
- The solution must allow the identification of which particular delivery is arriving earlier than expected (a material might have more than one delivery in transit, but some of them might be on time);
- The solution, supported by an analysis process, must allow the identification of possible root causes.

4.2.1 Developing a method to detect early deliveries

With the main objectives of the solution identified, the next step was to start conceiving a solution. The LOS team expressed the need to have a first solution implemented quickly. This presented an opportunity to implement a first solution that would allow the team to test the concept and could help understand if this could help to tackle the problem, as well as the limitations it has and what improvements could be done. The team identified the materials transported by sea as the ones that were most important to be included in this test since they are all delivered at the external warehouse and were the most critical ones at the time.

To detect early deliveries, the deliveries in transit have to be compared to the open orders to detect deviations. A simple example of how this can be done can be checked in Figure 11. By comparing the total quantities in transit, 23015 units, with the quantities ordered inside the PTF (that is, the quantities that should be in transit already), it is possible to detect that the supplier is sending a bigger quantity than ordered by Bosch, 18864 units. It is possible to conclude that more than 4000 units of this material are being delivered earlier than needed. Therefore, there is an early delivery.

ASN

Delivery	ExtDeliv.	Vendor	Material	Name of vendor	Purch.Doc.	Deliv.date	Delivery quantity
1800033930	20BC000002					14-06-2020	4 224
1800035092	20BC000004					20-06-2020	849
1800035098	20BC000005					26-06-2020	1 702
1800036238	20BC000007					13-07-2020	1 469
1800036249	20BC000009					08-07-2020	11 218
1800036919	20BC000010					15-07-2020	3 184
1800037836	20BC000011					22-07-2020	369
						Total	23 015

Open orders

Delivery date	Quantity	
09-06-2020	6 775	6 775
06-10-2020	2 268	9 043
17-11-2020	5 229	14 272
23-02-2021	1 326	15 598
04-05-2021	1 849	17 447
20-07-2021	1 417	18 864

Figure 11 - Example of material with early deliveries

With a conception of how early deliveries can be identified, the next step is to develop a solution that could give these capabilities to the company.

4.2.2 Data requirements and collection

With a solution proposal that can help identify early deliveries, by comparing open orders with deliveries, the next step is to identify the data that is necessary to achieve this, as well as its sources.

There are two main data groups needed: deliveries and orders data. These two data sources are the basis for the analysis. Also, other data was needed to support the analysis, such as information about the materials and suppliers. The majority of the data was collected from SAP, except for supplier data, which was stored in an excel file, as seen in Table 6.

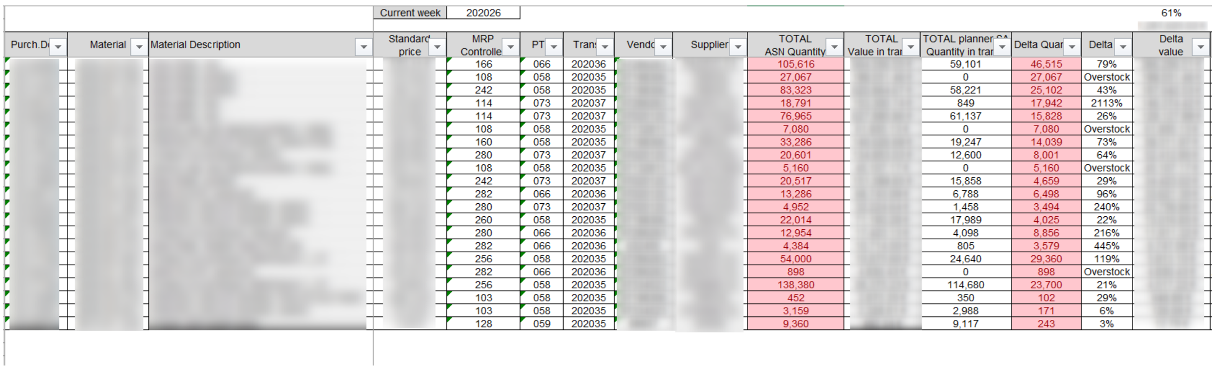
Table 6 – Necessary data and data sources

Necessary data	**Data sources**
Deliveries data (ASN)	SAP transaction VL06 – Inbound Delivery Monitor
Orders data	SAP transaction RB9S/PROC_DIS_QUANT – List Order Quantities
Material master data	SAP transaction RB04/2L3_MM_MATERIAL_EXTRACT – Material Master Extraction
Suppliers data	Supplier database (excel file)

The data fields used will be presented in a subsequent action, since a more complex and detailed data collection process is presented.

4.2.3 Developing the Early Delivery Detection Report (EDDR)

With the needed data identified, the next step is to develop the first EDDR. To test the idea, the first report was developed in an excel file. The data from SAP is extracted to excel files. Then these files as well as the Supplier database excel file are loaded into a unique excel file. There, using excel formulas, the data is combined and analysed to build the report. Weekly, the top 3 critical materials of each planner, considering the monetary value of the early deliveries, is chosen to be analysed by the planners, as seen in Figure 12. The idea is to test the report and at the same time to monitor the most critical materials, as it is impossible to focus on all materials with early deliveries.


Current week 202026 61%

Purch.D	Material	Material Description	Standard price	MRP Controlle	PT	Tran	Vendo	Supplier	TOTAL ASN Quantity	TOTAL Value in trar	TOTAL planner Quantity in trar	Delta Quar	Delta	Delta value
				166	066	202036			105,616		59,101	46,515	79%	
				108	058	202035			27,067		0	27,067	Overstock	
				242	058	202035			83,323		58,221	25,102	43%	
				114	073	202037			18,791		849	17,942	2113%	
				114	073	202037			76,965		61,137	15,828	26%	
				108	058	202035			7,080		0	7,080	Overstock	
				160	058	202035			33,286		19,247	14,039	73%	
				280	073	202037			20,601		12,600	8,001	64%	
				108	058	202035			5,160		0	5,160	Overstock	
				242	073	202037			20,517		15,858	4,659	29%	
				282	066	202036			13,286		6,788	6,498	96%	
				280	073	202037			4,952		1,458	3,494	240%	
				260	058	202035			22,014		17,989	4,025	22%	
				280	066	202036			12,954		4,098	8,856	216%	
				282	066	202036			4,384		805	3,579	445%	
				256	058	202035			54,000		24,640	29,360	119%	
				282	066	202036			898		0	898	Overstock	
				256	058	202035			138,380		114,680	23,700	21%	
				103	058	202035			452		350	102	29%	
				103	058	202035			3,159		2,988	171	6%	
				128	059	202035			9,360		9,117	243	3%	

Figure 12 - Report developed to analyse early deliveries

As seen in Figure 12, the report presents basic information about the material, such as the material identifier, the purchasing document, the supplier, the planner, and the information needed to identify the early delivery, such as the quantity in transit, the quantity ordered in the PTF, the extra quantity sent by the supplier and its value. The value of the early deliveries quantity is the criteria chosen to select the most critical materials.

The report is extracted and updated weekly, every Monday, with new information being added every week as new early deliveries occurred. The weekly Early Delivery Detection Report takes approximately 3 hours to be prepared, including the time to extract the data and prepare the analyses in excel. After generating the report, LOS planners had to check the information on the report to see if any materials under their responsibility had early deliveries. The planners had to investigate and indicate the root cause and take any actions. The goal is for them to identify the responsible for each early delivery (Bosch or the supplier). In case they concluded the early delivery was the responsibility of the supplier, they should request a Q2 claim to be issued. Other actions included but also notifying suppliers or requesting the supplier's delivery plan to check if there are any discrepancies in the next delivery, allowing them to prevent future early deliveries.

4.2.4 Lessons learned and conclusion

After implementing the EDDR, it was possible to conclude what were the advantages of the solution, the downsides and what improvements could be made.

The planners' feedback was extremely positive as they claimed they had more visibility over their inbound deliveries, which allowed them to detect early deliveries and act to prevent more in the future. By identifying materials with early deliveries, planners contacted suppliers and notified them of the early delivery. In some cases, planners requested the supplier for the deliveries plan and when identifying there were discrepancies with Bosch's order requests, would ask suppliers to correct their delivery plan according to Bosch's orders. By establishing this contact with suppliers, planners reported they were able to prevent future early deliveries.

From the EDDR implementation, it is possible to understand that using data analysis can support the detection of early deliveries. This detection was enabled by creating and implementing a report that, using the deliveries and orders data in SAP, allows the detection of the most critical materials with early deliveries. By detecting early deliveries, Bosch take actions that allow the company to mitigate its impact and prevent more from happening in the future.

As seen previously, the report achieved good results with the reduction of the percentage of materials with early deliveries, as well as the value of early deliveries. The main advantages of this action are:

- Enabling the detection of materials with early deliveries;
- Identify the most critical materials by quantifying the quantity being delivered earlier than ordered and its value;

- Increases visibility, allowing planners to be aware of what is happening with supplier deliveries;
- By identifying critical materials, it enables planners to take actions and prevent future early deliveries.

Despite the results and benefits achieved, that allows the team to understand that this approach can help tackle the early deliveries problem, there are still several issues that need to be addressed and improved:

- **Difficulty to identify early deliveries:** the report does not allow planners to identify which specific delivery is arriving earlier than expected, but only the total value from the various deliveries that the supplier is sending. This information is extremely important for the planner to know when the early delivery is expected to arrive, something that is not possible with the report. To check this information, planners need to go to an SAP transaction to check for the inbound deliveries, and then compare them manually with the open order, checked in a different transaction. This a difficult task, since delivery is not necessarily a direct match with an order. An example such as this can be seen in Figure 11, where there are 7 deliveries for 6 orders. As it is possible to see, it is difficult to check which of the 7 deliveries is arriving on the wrong date and with how many days in advance. Therefore, it is essential to develop a visualisation that facilitates this work to the planners and allows them to quickly identify the exact early deliveries and their arrival date;
- **Lack of tools and a process to detect the root cause of early deliveries:** Another problem reported is the lack of support to identify the cause of the early delivery. As will be seen further ahead (section 4.4.1), planners need to identify the cause of an early delivery to understand whether it was Bosch's or supplier's responsibility and how they should act (issue a Q2 claim to the supplier or not, for example). Planners claim to lose a significant amount of time investigating the root cause and the lack of a guide with the steps to be followed. This means that the solution presented fails to help address problems 3 and 4. Therefore, is it essential to develop analysis tools to analyse data and a standard process that will guide planners in analysing their critical materials, saving them precious time;
- **Time to prepare the EDDR:** the EDDR was prepared every Monday manually by the authors of this dissertation. The report took approximately 3 hours to be prepared, including the time to extract all the data from SAP, preparing the data in excel, building the report and verifying the accuracy and correctness of the report. The fact that several steps are done manually increased the chances of errors, which implicated correcting them, meaning more time would

be wasted. This is not sustainable and might compromise the long term success of the solution since it requires Bosch to allocate resources in the future to keep the report. Therefore, it is crucial to improve the preparation and data analysis process by automating it.

- **Data refresh problems:** the report is only prepared once a week, on Mondays. This meant that information in the following days may not reflect its current status. Updating the report daily is not feasible, since it will take at least 3 hours daily. Therefore, once again it is proven that it is necessary to automate this process.
- **Data handling problems:** another problem is the capacity of Excel to deal with relatively large volumes of data. The report is capable of dealing with the data and performs well. However, it is important to mention that only sea suppliers are included in the report. Also, in the future, as the supply chain adapts to new circumstances, there might be a need to process larger volumes of data. Therefore the software used must be capable of adapting and processing larger volumes of data.

To sum up, it is possible to confirm that the first report tested brings benefits and helps the company addressing the early deliveries problem. However, several obstacles and problems were identified, that need to be tackled. Therefore, in the following actions, it is essential to address these issues, building a sustainable solution that can help the company in the long term.

4.3 Developing a BI&A solution for early delivery detection and analysis

As presented in section 4.2, the three problems that are being addressed are problems 2, 3 and 4, which are are intrinsically connected.

Based on these problems, different objectives have been defined:

- The solution must allow the detection of materials with early deliveries while they are in transit;
- The solution must quantify the early delivery (in quantity and value) and allow the prioritisation of the most critical materials;
- The solution must allow the identification of which particular delivery is arriving earlier than expected (a material might have more than one delivery in transit, but some of them might be on time);
- The solution, supported by an analysis process, must allow the identification of possible root causes.

As presented in section 4.2.3, the EDDR showed that it is possible to detect early deliveries and quantity its impact in terms of overdelivery quantity and monetary value. However, some problems remain unaddressed and therefore require solutions. There is still the need to be able to analyse in detail a material to understand which deliveries are a deviation from the order plan instead of only having a high-level view of the material. Simultaneously, there is also the need to support the responsibility analysis with BI&A, by efficiently enabling the use of data, and with a clear, simple and effective analysis process. Furthermore, some technical difficulties need to be addressed. The excel report is manually prepared weekly, taking around 3 hours to be available. Also, the fact that it lacks automation processes makes it error-prone. There is also the data refresh problem. Since the report is prepared only once a week, the data is not always updated, which might lead to outdated information being processed by the users. Finally, it is important to develop a solution capable of handling well with relatively large volumes of data, cleaning and analysing them without any problems, something Excel is not designed for.

Considering all the ideas stated above, it is important to develop an efficient and sustainable solution capable of helping the company identifying and analysing early deliveries, by gathering, preparing and analysing data.

With the objectives and problems attempting to be tackled defined, the development of the BI&A solution is started. An overview of the developed BI&A solution is presented in Figure 13. As seen, the data is extracted from DALI, which is an internal database that stores data from SAP. This information is extracted using Structured Query Language (SQL). The application used to develop the solution is Power BI, developed by Microsoft. It is available in Bosch for open use and can develop dashboards capable of extracting large volumes of data from multiple sources, clean, analyse and present it with appealing visuals for the user to analyse. After the extraction of data to Power BI, the data is prepared and simple transformations are done, after which the data is loaded for analysis. In the analysis step, different math operations are applied to get the insights needed. Finally, the analysed data is presented through different visuals and reporting, allowing the users to get information gain intelligence regarding their inbound deliveries. The solution is automated and updates the information automatically daily, requiring human intervention solely for maintenance operations.

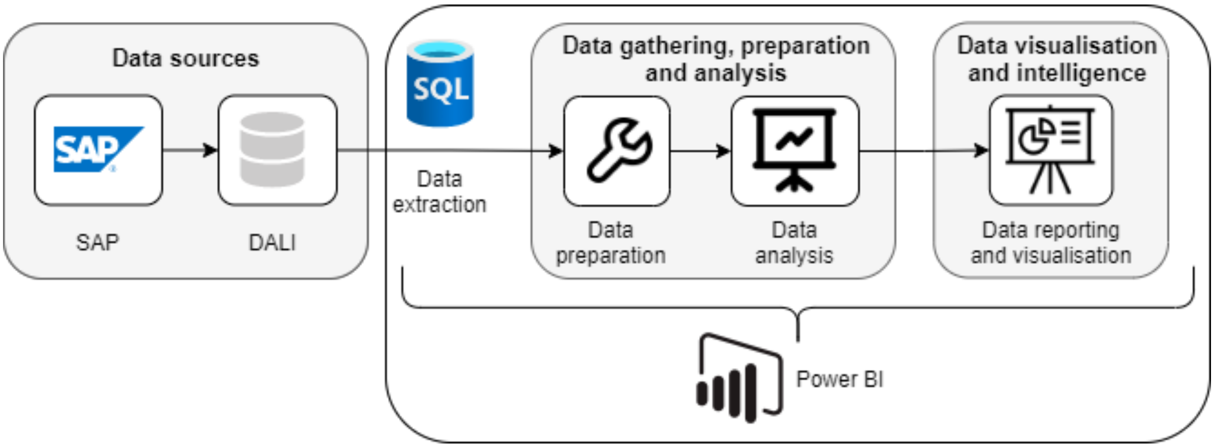


Figure 13 - Diagram of the different components of the BI&A solution

The different steps and stages of the development of this solution are presented and detailed next.

4.3.1 Data requirements and data collection

The first step was to identify the data requirements of the solution. The necessary data fields and their tables were identified in DALI. Different datasets with different information about inbound supply operations are needed, such as data from deliveries, data from orders, from materials' characteristics, among others. The different datasets needed are:

- Purchasing Document dataset: contains data about the purchasing documents, such as the material, the supplier or the incoterms;
- Orders dataset: contains the data about the current orders Bosch has sent to suppliers, such as the ordered quantities and dates;
- Material Master dataset: contains the basic information about the materials, such as price, PTF and the MRP the material is allocated to;
- Deliveries (ASNs) dataset: contains the data about the ASNs, which have the information about the deliveries, such as the quantity being delivered, ETD and ETA;
- Order Releases dataset: contains the information about the order releases, i.e., about the releases sent in the past to suppliers, with the ordered quantities and dates;
- Material Receipts dataset: contains the information about the reception of materials at the warehouse, which contains information about the reception date and received quantities of materials.

With the needed datasets identified, the next step was to identify the necessary data and its location in DALI, i.e., the table the data is stored and the name of the field. After identifying this information, the possible connections between tables were studied to understand how tables could be joined using SQL. In this step, the columns on which the Joins would be based and their combination are identified. A query diagram was built for each dataset detailing the connections between the tables and the columns needed to make the joins. With this information, the SQL queries were written to extract the data from the system. These last two steps form an iteration since writing the queries and analysing their results would allow to better identify the possible connections between the tables. This process is systematic and is represented in Figure 14.

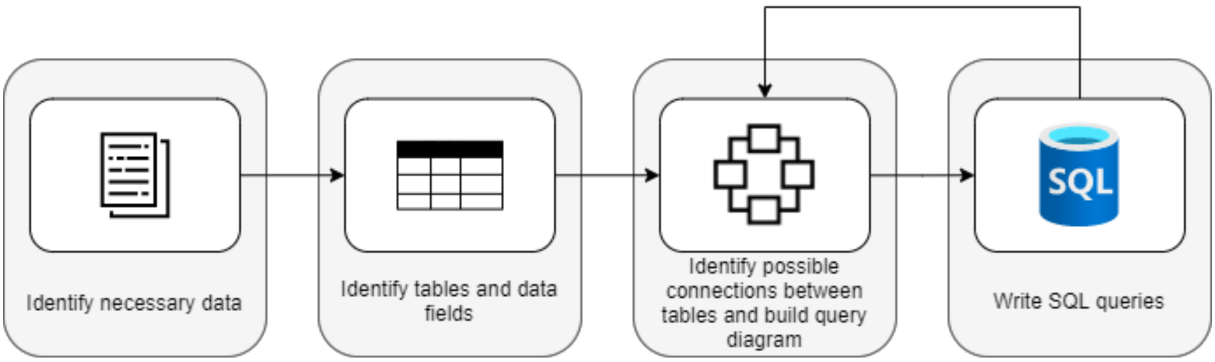


Figure 14 - Data identification and gathering process

An example of this process application is presented using the Purchasing Documents dataset. Purchasing document data contains information regarding the schedule agreement with the supplier. As mentioned before, each purchasing document is given to each material from each supplier, i.e., a purchasing document corresponds to one material and one supplier. Purchasing documents contain information about the material and the supplier. The necessary data and its fields, as well as the table in DALI where it is stored, is listed in Table 7. The table contains not only the attributes necessary for analysis but also the fields that were identified as necessary to filter data.

Table 7 - Purchasing document dataset: list of attributes and fields identified

Name	Description	Field name	Tables names
Purchasing Document	Purchasing document number	EBELN	EKPO, EKKO
Item	Item number of purchasing document	EBELP	EKPO
Material	Material number	MATNR	EKPO, MARC
Consignment indicator	Indicator of the existence of consignment	PSTYP	EKPO
ASN indicator	Indicator of ASN implementation	BSTAE	EKPO
Firm zone	Period of production release	ETFZ1	EKPO
Trade-off zone	Period of material release	ETFZ2	EKPO
Plant	Bosch plant code	WERKS	EKPO, MARC
Deletion indicator	Deletion indicator in Purchasing Document	LOEKZ	EKPO
Vendor	Supplier identification code	LIFNR	EKKO, LFA1
Incoterm	Incoterm adopted	INCO1	EKKO
Incoterm information	Incoterm detailed information	INCO2	EKKO
Purchasing organisation	Purchasing organisation code	EKORG	EKKO
Purchasing document type	Purchasing document type code	BSART	EKKO
Supplier	Supplier name	NAME1	LFA1
MRP type	MRP type code	DISMM	MARC

With the attributes identified, the next step was to understand the connection between the tables. The combination of columns to join the tables are identified. This step is important as understanding how the tables and the data can be linked is essential for successfully developing the query to form the dataset. Query diagrams were developed with the connections of tables, as well as the keys on which the joins are made. The query diagram of the Purchasing Documents dataset can be checked in Figure 15.

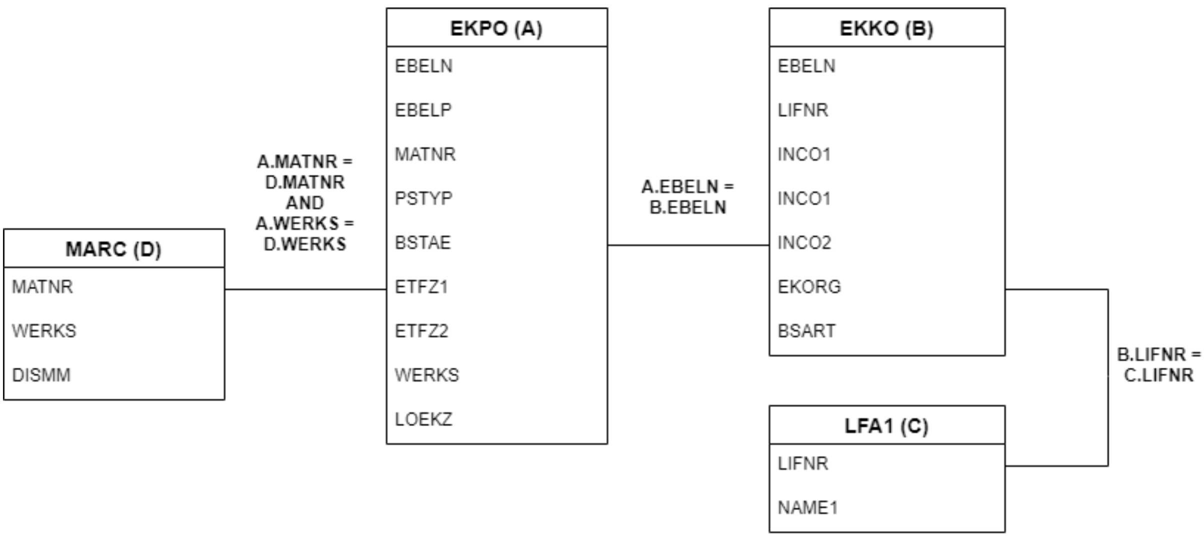


Figure 15 - Query diagram of Purchasing Document dataset tables

With the identified fields and filters, the next step was building the SQL query that would allow the extraction of the needed data from the database. The query for the Purchasing Document dataset is shown in Figure 16.

```
SELECT A.EBELN as PurchDoc, A.MATNR as Material, A.EBELP as ITEM, A.PSTYP as Consign, A.ETFZ1 as FirmZone,
A.ETFZ2 as TradeOffZone, B.LIFNR as Vendor, C.Name1 as Supplier, B.INCO1 as Incoterm1, B.INCO2 as Incoterm2
FROM [illegible].EKPO_P45 A
LEFT JOIN (SELECT EBELN, LIFNR, INCO1, INCO2, EKORG, BSART
          FROM [illegible].EKKO_P45) B
          ON (A.EBELN = B.EBELN)
LEFT JOIN (SELECT LIFNR, NAME1
          FROM [illegible].LFA1_P45) C
          ON (B.LIFNR = C.LIFNR)
LEFT JOIN (SELECT MATNR, DISMM, WERKS
          FROM [illegible].MARC_P45) D
          ON (A.MATNR = D.MATNR AND A.WERKS = D.WERKS)
WHERE A.WERKS = '8150'
  AND A.LOEKZ = ' '
  AND (B.EKORG = '4991' OR B.EKORG = 'LOGA')
  AND B.BSART = 'LPA'
  AND A.BSTAE = '0004'
  AND D.DISMM <> 'YI'
```

Figure 16 - SQL query to extract the Purchasing Document dataset

This process is repeated for the other datasets. The tables and the necessary fields, the query diagrams and their SQL queries can be checked in Appendix 1 – Data requirements and collection.

4.3.2 Data preparation and data analysis

A connection to DALI is created on Power BI and, with the SQL queries, the data is extracted to the application. The next step is to prepare the data for analysis. Most of the data does not require any preparation, since the unnecessary data fields were not included in the queries and the ones that are included do not have big quality problems. Some simple data transformation operations were applied. For instance, for the Deliveries (ASN) dataset, the data format for the dates was changed, since they are stored in DALI as strings, as in Power BI they are changed to date type. The sequence of transformations for this dataset is displayed in Figure 17. For the other datasets, the operations were similar. These steps are performed in Power Query, an available resource for data preparation in Power BI.

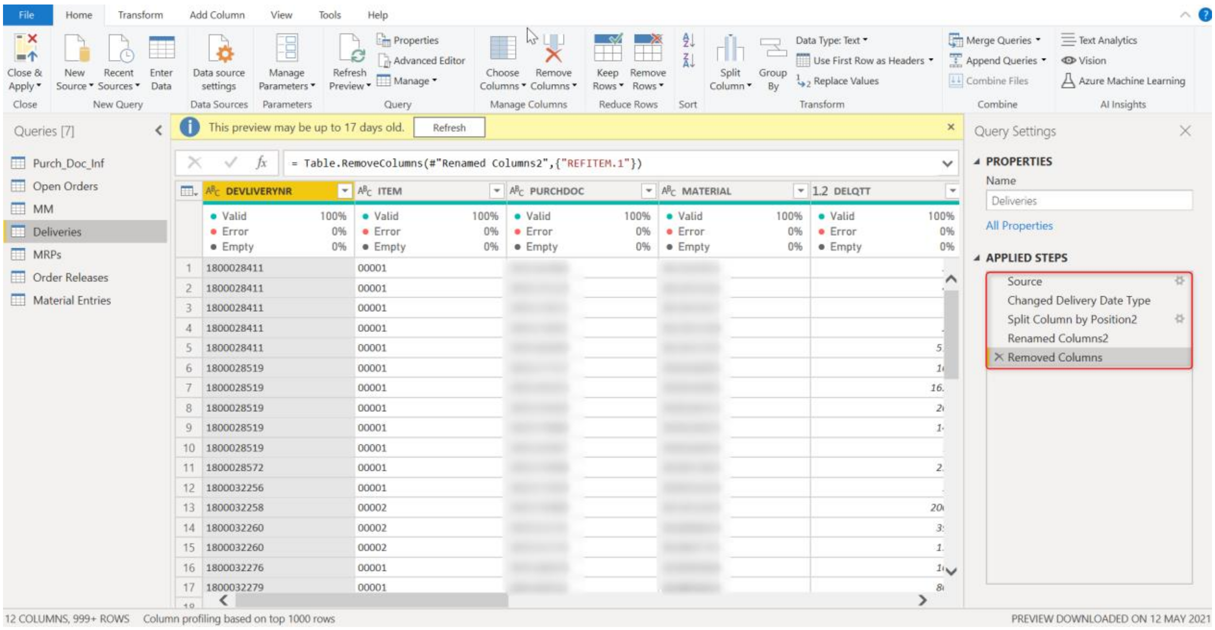


Figure 17 – Data preparation for the Deliveries (ASN) dataset

With the data prepared to be analysed, the next step is loaded for analysis. Before starting the data analysis, the data model is created, with the connections between datasets (Figure 18). This step is necessary since the different datasets (or tables) need to be connected to navigate between them and perform analyses with data from across different tables.

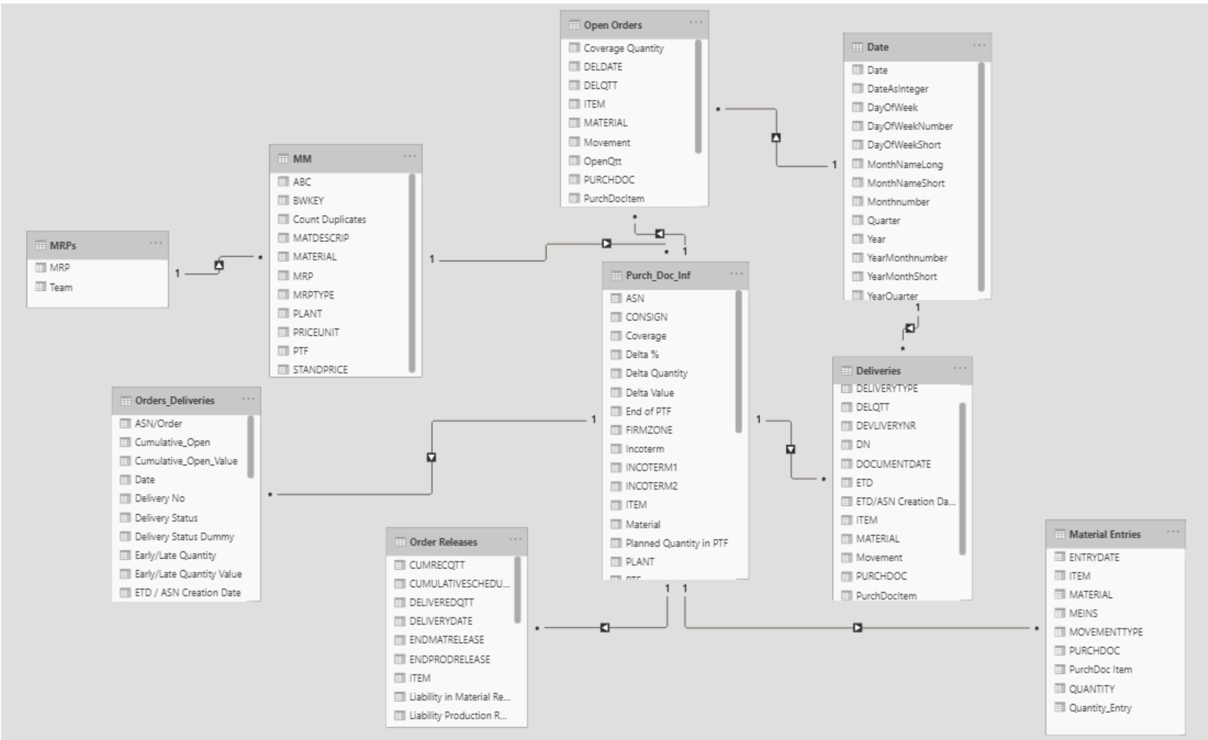


Figure 18 - Data model in Power BI

With everything set, data analysis is carried out. To conduct the data analysis, Data Analysis Expressions (DAX)[1] is used. DAX is a formula language included in Power BI that allows users to carry out data analysis, allowing them to work with relational data and perform dynamic aggregation. The analyses that were carried out are the basis of the information and visuals that are displayed to the user in the dashboard, which will be presented in the next section (section 4.3.3). The DAX formulas that were created can be checked in Appendix 2 – DAX formulas. These formulas result in calculated columns, that are added to the tables, or in measures, that are independent of the tables.

4.3.3 Data reporting and visualisation

The next step was developing the dashboard that allowed data reporting and visualisation. The dashboard has 5 different tabs (Appendix 3 – Dashboard tabs). The first tab (Figure 19) presents basic information about the dashboard, explaining its purpose and contents. It contains hyperlinks that allow users to navigate between the different tabs. It also allows the user to report any failure or error in the dashboard.

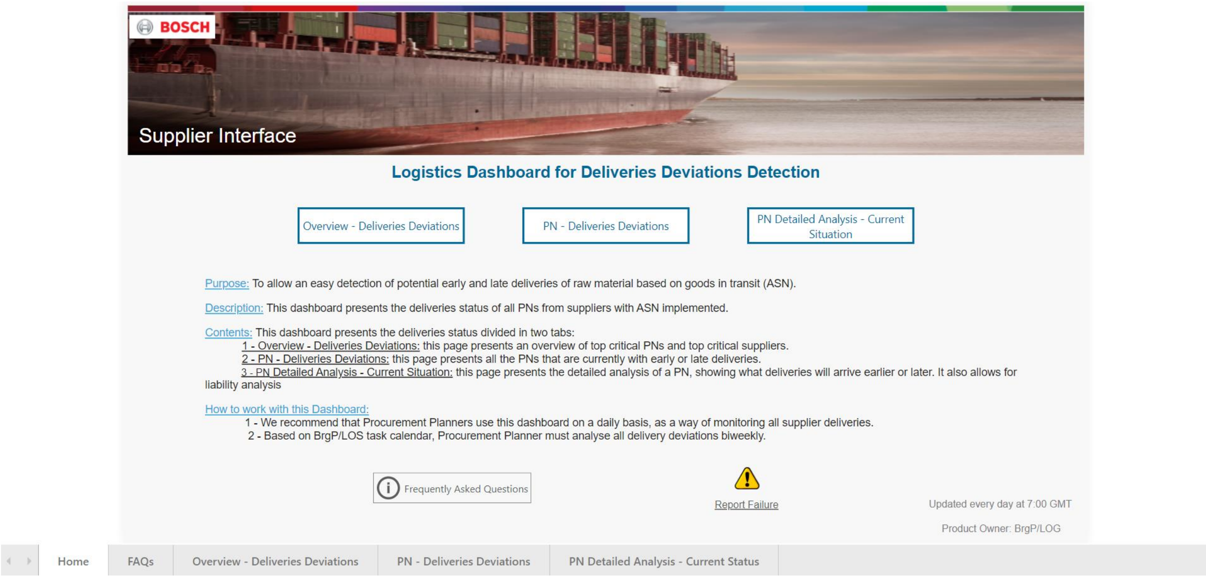


Figure 19 - First tab: Home

The second tab of the dashboard (Figure 20) presents some Frequently Asked Questions (FAQs) about the dashboard. These questions include information regarding the data that is being used and the information presented on the dashboard.

[1] DAX: https://docs.microsoft.com/en-gb/power-bi/transform-model/desktop-quickstart-learn-dax-basics

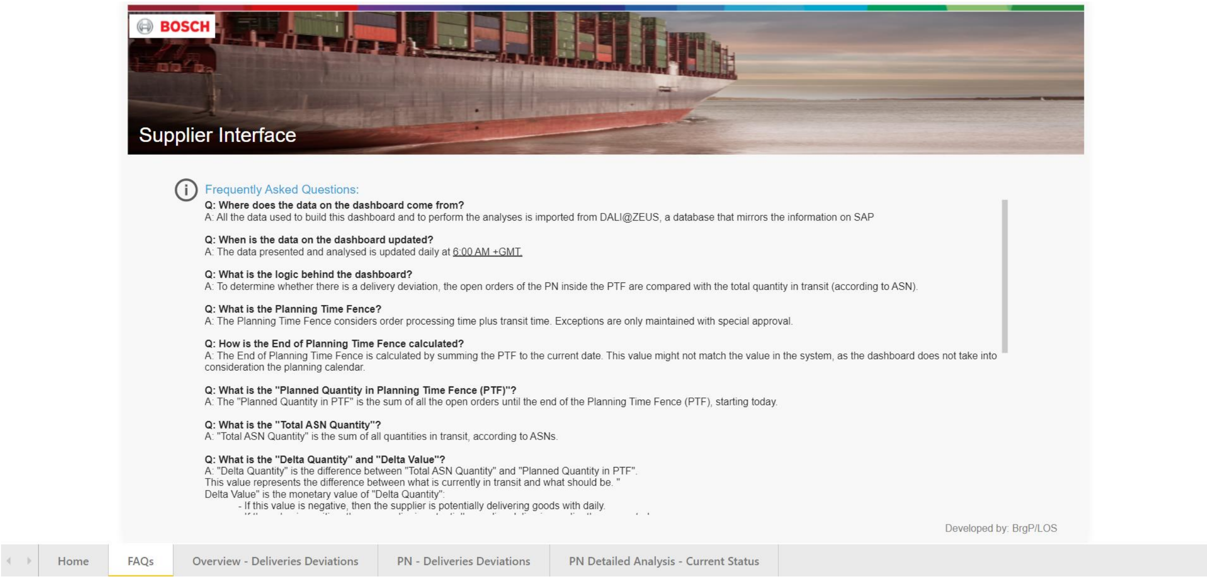


Figure 20 – Second tab: FAQS

The remaining 3 tabs of the dashboard are the ones that present the information to be analysed by planners regarding early deliveries. The third tab presents an overview of the current status of early deliveries.

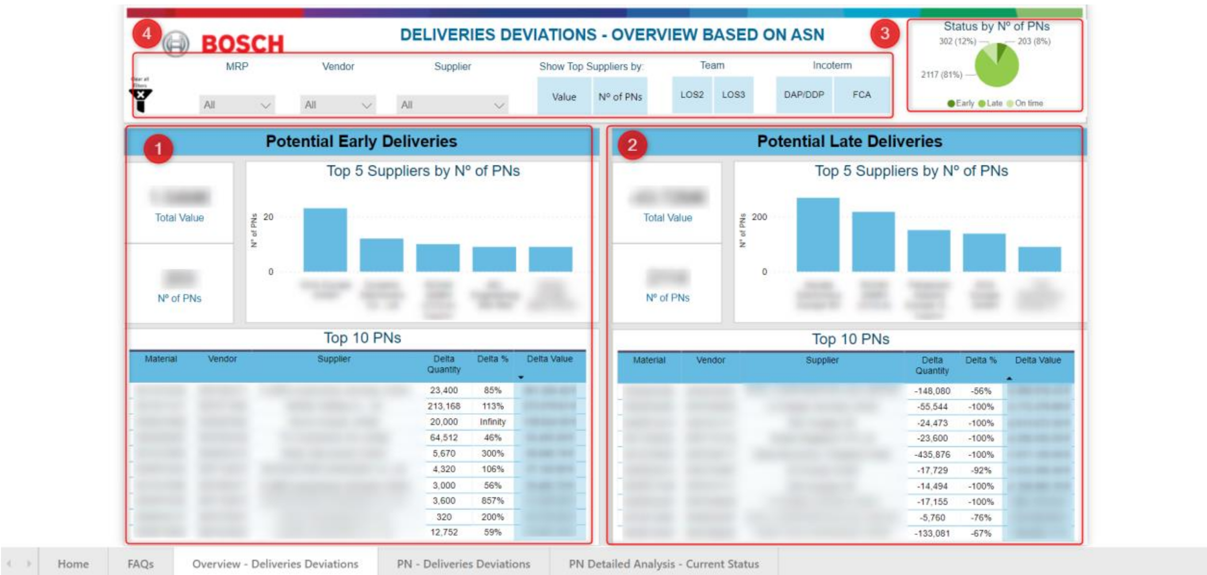


Figure 21 - Third tab: Overview - Delivery Deviations

As seen in Figure 21, this tab presents an overview of the current status of the materials that have early deliveries. This tab is divided into 4 areas, as signalled in Figure 21:

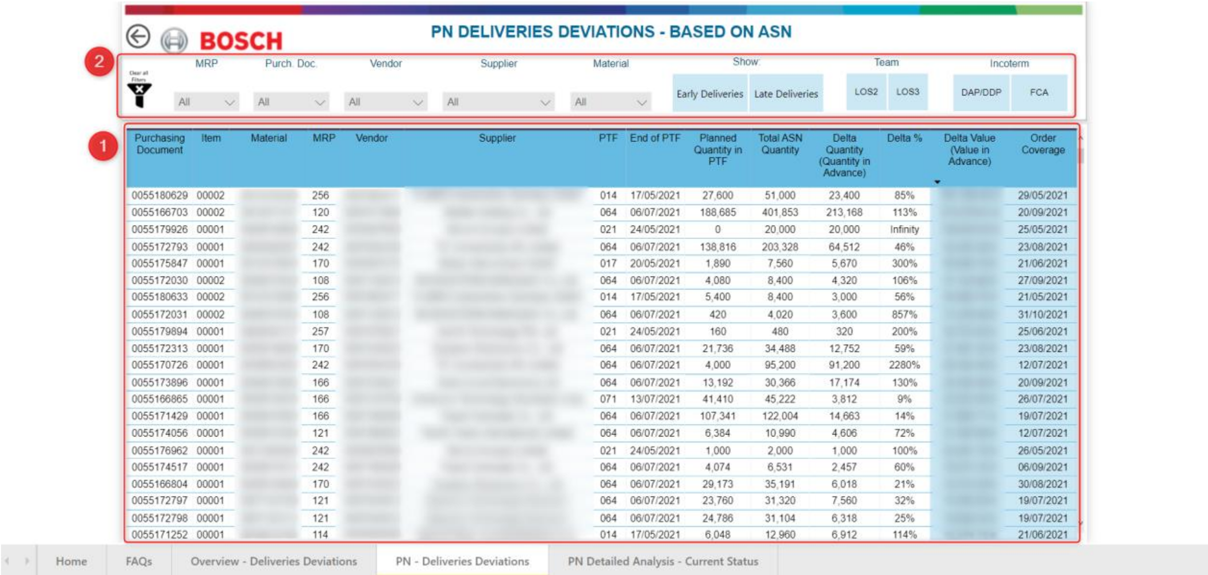
1. The first area presents an overview of the potential early deliveries detected by the solution. Here, users can check the total value of early deliveries that are in transit as well as the number of PNs with early deliveries. Simultaneously, the top 10 critical PNs with the most

valuable early deliveries are displayed in a table, with the basic information about the supplier and regarding how much more is being delivered and its value. Lastly, a graph with the 5 suppliers with the most valuable early deliveries or with most PNs with early deliveries, according to the filter option selected in area 4.

2. The second area of the dashboard presents information regarding late deliveries. Despite not being the focus of this dissertation, the data used to detect early deliveries also allow the detection of late deliveries. The company already has other support tools that allow them to monitor late deliveries. However, this solution enables the detection of late deliveries in a more timely manner, since it displays more long-term information than the other tools. Therefore, this information was also included as it complements the other available tools the company has, increasing their visibility over late deliveries. The information presented regarding late deliveries is the same as the one presented for early deliveries.
3. The graph presented in signalled area 3 presents an overview of the overall status of PNs, stating the percentage of PNs according to their status (on-time, late or early deliveries).
4. Signalled area 4 presents several filters to the user. By filtering the information according to the available filters, the dashboard adapts the information displayed accordingly. Users may filter according to an MRP, Vendor code, Supplier name, team (LOS2 or LOS3) and incoterms. It also allows selecting whether they want to see the 5 most critical suppliers by early/late deliveries value or by the number of PNs.

With the information of this tab, the company can identify the most critical suppliers and materials that might worth focusing on for improvement actions.

The fourth tab of the dashboard displays a list of all the PNs with delivery deviations. Here, users can find information about materials with early deliveries and quantity the deviation.



Purchasing Document	Item	Material	MRP	Vendor	Supplier	PTF	End of PTF	Planned Quantity in PTF	Total ASN Quantity	Delta Quantity (Quantity in Advance)	Delta %	Delta Value (Value in Advance)	Order Coverage
0055180629	00002	[illegible]	256	[illegible]	[illegible]	014	17/05/2021	27,600	51,000	23,400	85%	[illegible]	29/05/2021
0055166703	00002	[illegible]	120	[illegible]	[illegible]	064	06/07/2021	188,685	401,853	213,168	113%	[illegible]	20/09/2021
0055179926	00001	[illegible]	242	[illegible]	[illegible]	021	24/05/2021	0	20,000	20,000	Infinity	[illegible]	25/05/2021
0055172793	00001	[illegible]	242	[illegible]	[illegible]	064	06/07/2021	138,816	203,328	64,512	46%	[illegible]	23/08/2021
0055175847	00001	[illegible]	170	[illegible]	[illegible]	017	20/05/2021	1,890	7,560	5,670	300%	[illegible]	21/06/2021
0055172030	00002	[illegible]	108	[illegible]	[illegible]	064	06/07/2021	4,080	8,400	4,320	106%	[illegible]	27/09/2021
0055180633	00002	[illegible]	256	[illegible]	[illegible]	014	17/05/2021	5,400	8,400	3,000	56%	[illegible]	21/05/2021
0055172031	00002	[illegible]	108	[illegible]	[illegible]	064	06/07/2021	420	4,020	3,600	857%	[illegible]	31/10/2021
0055179894	00001	[illegible]	257	[illegible]	[illegible]	021	24/05/2021	160	480	320	200%	[illegible]	25/06/2021
0055172313	00001	[illegible]	170	[illegible]	[illegible]	064	06/07/2021	21,736	34,488	12,752	59%	[illegible]	23/08/2021
0055170726	00001	[illegible]	242	[illegible]	[illegible]	064	06/07/2021	4,000	95,200	91,200	2280%	[illegible]	12/07/2021
0055173896	00001	[illegible]	166	[illegible]	[illegible]	064	06/07/2021	13,192	30,366	17,174	130%	[illegible]	20/09/2021
0055166865	00001	[illegible]	166	[illegible]	[illegible]	071	13/07/2021	41,410	45,222	3,812	9%	[illegible]	26/07/2021
0055171429	00001	[illegible]	166	[illegible]	[illegible]	064	06/07/2021	107,341	122,004	14,663	14%	[illegible]	19/07/2021
0055174056	00001	[illegible]	121	[illegible]	[illegible]	064	06/07/2021	6,384	10,990	4,606	72%	[illegible]	12/07/2021
0055176962	00001	[illegible]	242	[illegible]	[illegible]	021	24/05/2021	1,000	2,000	1,000	100%	[illegible]	26/05/2021
0055174517	00001	[illegible]	242	[illegible]	[illegible]	064	06/07/2021	4,074	6,531	2,457	60%	[illegible]	06/09/2021
0055166804	00001	[illegible]	170	[illegible]	[illegible]	064	06/07/2021	29,173	35,191	6,018	21%	[illegible]	30/08/2021
0055172797	00001	[illegible]	121	[illegible]	[illegible]	064	06/07/2021	23,760	31,320	7,560	32%	[illegible]	19/07/2021
0055172798	00001	[illegible]	121	[illegible]	[illegible]	064	06/07/2021	24,786	31,104	6,318	25%	[illegible]	19/07/2021
0055171252	00001	[illegible]	114	[illegible]	[illegible]	014	17/05/2021	6,048	12,960	6,912	114%	[illegible]	21/06/2021

Figure 22 - Fourth tab: PN - Delivery deviations

As seen in Figure 22, users are presented with a table, signalled with as 1. This table contains all the basic information about the status of the material. It presents the basic information of the material (such as its number, purchasing document or supplier), as well as the information needed to analyse the PN. This information includes the quantity ordered, the quantity that is in transit according to the ASNs, the delta quantity (which is the difference between what is in transit and what has been ordered, i.e., the deviation quantity), the delta value (the value of the delta quantity) and the order coverage (the date until which the quantities in transit cover all the orders). The area signalled as 2 presents some filters for the users to search for the information needed. For instance, a LOS planner wants to filter the information to display only the materials that are assigned to his/her MRPs.

With the information available on this tab, the company can identify the status of all materials, detecting early deliveries while they are in transit, as well as quantifying those early deliveries in terms of quantity, value or time coverage.

Finally, the fifth tab displays a detailed analysis of the situation of each material (Figure 23).

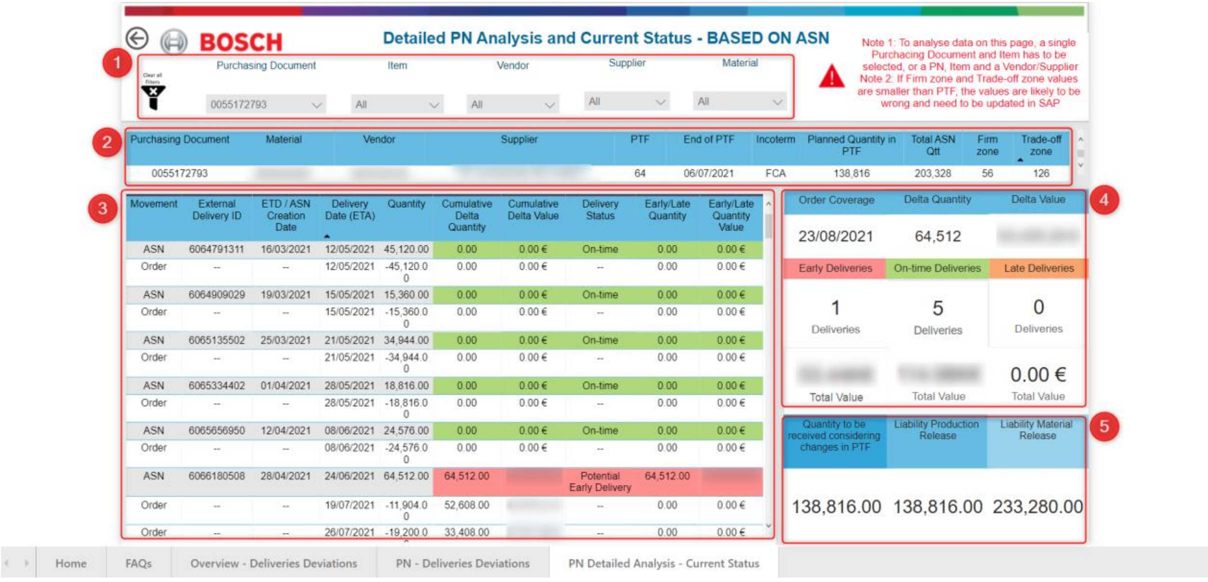


Figure 23 - Fifth tab: PN detailed analysis

As seen in Figure 23, the tab allows analysing in detail a specific PN for a specific supplier. The user must select the Purchasing Document (PN and supplier) he/she wishes to analyse, using the filters signalled in Figure 23 as 1. The area signalled with number 2 presents some basic information about the material, such as the Purchasing Document number or the supplier.

The area signalled with the number 3 presents a table with a detailed analysis of all the deliveries and open orders for the material and supplier selected. As seen in Figure 23, the solution identifies automatically the status of each delivery, stating whether it is an on-time, late or early delivery. With this information, LOS planners identify which specific delivery is a deviation and can identify when it will arrive and how many days earlier than expected. This visual allows planners to efficiently monitor their material deliveries.

The area signalled with the number 4 presents an overview of the status of the material, showing the order coverage of the quantities in transit, how much more is being delivered by the supplier and the value of that extra quantity. Simultaneously, it counts how many deliveries are on-time, late and early, and the value of those deliveries.

Finally, the area signalled by the number 5 displays information about order changes and order liability. This area allows planners to check how much quantity they are obliged to receive considering order changes inside the PTF. If the information displayed shows that Bosch has to receive more quantity than currently ordered, the planners may conclude that there were order changes inside the PTF and the early delivery is the responsibility of Bosch. This task was previously done by analysing if there were any order reductions or cancellations inside the PTF in the past order releases and was done manually, using a transaction in SAP that allows users to compare order releases. Planners reported losing around 30 minutes in each material comparing different weekly releases to detect if there were any order changes. With the new functionality in the dashboard, it takes just seconds. Planners may also analyse production and material liability, which was an analysis that also took around 30 minutes. These functionalities allow planners to check for possible causes of early deliveries which helps to identify who is responsible for the early delivery. This responsibility analysis is supported by an analysis process, that will be presented further ahead.

4.3.4 Lessons learned and conclusion

The BI&A solution developed has several advantages and brought significant improvements. With the EEDR in excel, several difficulties were reported by LOS planners. Planners were able to detect materials with early deliveries but could not identify which specific delivery was arriving earlier and how many days earlier. Planners still had to check deliveries in SAP to check their arrival date and compare them manually with the open orders. Simultaneously, planners had to verify the responsibility of the early delivery manually on SAP, checking for different possible internal causes, namely order changes inside the PTF. With the new BI&A solution, they have a support tool that allows them to quickly analyse this internal cause. Planners reported they could carry out a detailed analysis of early deliveries more efficiently and in less time, without the need to check for other information in SAP. The Power BI solution offers a much wider range of functionalities and information, making it extremely easy for LOS planners to carry a detailed and full analysis of early deliveries in a significantly shorter amount of time. Planners reported wasting around 30 minutes analysing an early delivery with the EDDR excel file, while with the BI&A solution in Power BI this reduced to under 5 minutes.

Also, there were some technical problems with the EDDR excel file. The EDDR took around 3 hours weekly to be prepared and had to be updated every week. With the adoption of Power BI, the data refresh is done automatically every morning, without interfering with its use. Simultaneously, if the company wishes to increase the number of daily data refreshes in the future, it is also easily done.

With the new BI&A solution, it is now possible to turn data that was previously scattered in the system into information, generating meaningful insights and intelligence, by increasing visibility over the supply chain.

4.4 Supporting the BI&A solution with an analysis process

With the BI&A solution developed, data analysis was much accessible and easier, allowing planners to detect and identify early deliveries. However, to successfully address the early deliveries problem, it is important to take action. To do that, Bosch must identify the responsible for the occurrence of an early delivery, either Bosch or the supplier. The BI&A solution supports the analysis of some possible causes that help to identify who bears responsibility. This tackles problem 2 and partially tackles problems 3 and 4. However, it is important to support the use of this tool with a standardised analysis process, ensuring that every LOS planner follows the same procedure. Therefore, there is the need to support the BI&A solution on an analysis process, that allows the company to successfully tackle problems 3 and 4, as mentioned in section 3.3.3.

4.4.1 Detecting the causes and responsibility of early deliveries

To create a new analysis process, there was the need to understand what kind of causes there were for early deliveries to occur. Throughout the entirety of the project, each LOS3 planner analysed their top 3 materials transported by sea to identify the cause and responsibility of the early delivery. This allowed Bosch to decide what actions to take regarding early deliveries, but also to understand what information should be checked when analysing early deliveries. Planners attended a weekly meeting with the author where they would present the analysis carried out on the materials with early deliveries identified and present the cause for the material identified as having early deliveries.

The planners identified different causes that might lead to early deliveries occurring. The causes identified were:

- **Order changes inside PTF**: this occurs when Bosch changes orders requests inside the PTF. As explained in section 3.2.1, orders inside the PTF are already supposed to be in transit. Therefore, Bosch cannot change orders in the PTF unless specifically agreed with the supplier. Changing orders in the PTF will lead to the report identifying bigger quantities being delivered than the orders displayed in the system and signalling the material as having early deliveries;
- **Order not inserted in SAP**: this occurs when Bosch would place an exceptional order to the supplier via email, for example, but would not register the order in the system. There were three types of situations where orders not inserted in the system were identified:
    1. **Air freights (iStars)**: when there is a delivery delay and a second delivery, an air freight, has to be made for the materials to arrive on time to Braga. This means that two deliveries are being made for the same order. When an air freight is requested to the supplier, the new order placed must be registered in the system,

otherwise, the report will signal an early delivery, since there are two deliveries for the same order;

2. **Engineering Change Request (ECR) – risk order**: this situation occurs when the material is subject to an engineering change and a new order for the material is placed, but not registered in the system. An example of an ECR is a product that has its colour requirement changed, and therefore an order must be placed for the new material with the new colour;
3. **Material transferred from the Purchasing department (PPM)**: before the materials start being managed by LOS, they are under PPM's responsibility. This department is responsible for raw materials before a project enter the Start of Production (SOP) phase. Before that phase, some first orders are placed by PPM for example, for samples quality testing. Sometimes, materials transition from PPM to LOS with orders placed, but they are not in the system. Therefore, the report finds deliveries without any orders and detects early deliveries.

- **PTF data field not maintained in SAP**: this occurred for materials that did not have the PTF data field correctly maintained in SAP. This value is needed to calculate the quantity of a certain material that should be in transit. Therefore, if this value is not correct, the data analysis will not be accurate and will lead to false early deliveries being signalled;
- **ASN errors**: the report gets deliveries data from the ASNs. If any mistakes or any problems processing the ASNs occur, this will lead to the report analysing early deliveries incorrectly, leading to wrong materials being identified as early deliveries;
- **Bosch's liability:** as explained previously, Bosch is liable for material quantities ordered during a certain period in case any orders are cancelled. In case orders are cancelled within the production release, the supplier must notify Bosch and the company must accept receiving the cancelled quantities, and negotiate when the quantities should be delivered. When the supplier sends the quantities, there are no orders, leading to the report identifying an early delivery.

These causes are all internal causes. Identifying if there were any internal causes is extremely important, since Bosch cannot issue Q2 claims or ask suppliers to bear the responsibility if the early delivery was caused by Bosch's actions. If no internal cause for Bosch's deliveries is found, the supplier is considered responsible for the early delivery. However, identifying the root cause for suppliers sending early deliveries is extremely difficult since it requires an analysis of suppliers' internal processes and actions. Such depth of analysis is not possible and is not the focus of this project. Throughout the project, a total of 148 materials with early deliveries were analysed to detect whether there were any internal causes or if they were the supplier's responsibility. Figure 24 shows the distribution of the causes/responsibility of the early deliveries.

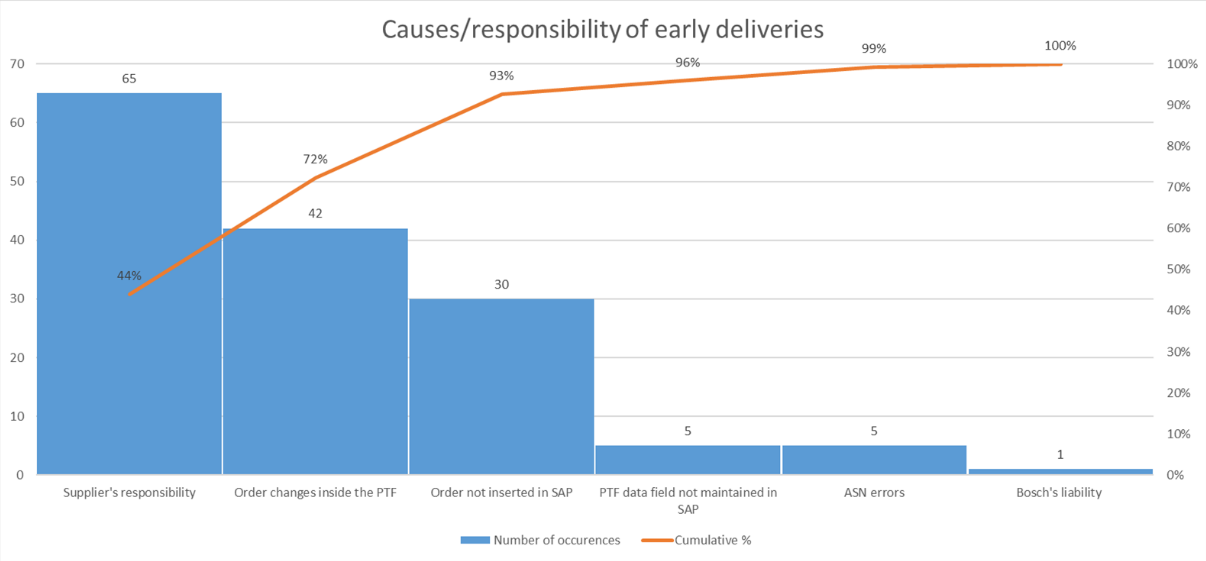


Figure 24 – Causes/responsibility of analysed early deliveries

Suppliers were found responsible for 65 of the 148 materials with early deliveries analysed, almost half of the early deliveries. The two main internal causes for early deliveries were order changes inside the PTF (42 occurrences) and orders that were not inserted in SAP (30). These two internal causes, along with early deliveries that are the supplier's responsibility, represent over 90% of early deliveries. Therefore, since these two causes were the most common, it was important to understand how could planners be assisted when analysing these two root causes.

Orders changes inside the PTF was the cause that has the most potential to be improved with data analytics and intelligence since it requires analysis of data that is in SAP. Therefore, it was included in the BI&A solution, as seen in section 4.3.3. On the contrary, checking for orders not inserted in SAP is relatively quick, since planners are usually aware of materials with air freights, ECR or recently transferred from PPM. The latter two, especially, are rare and punctual events that do not occur daily. Also, this task is difficult to be assisted by BI&A tools, since information is not SAP or any other system, but spread across several sources, such as emails.

Knowing the most common internal causes provides valuable insights for developing an analysis process. With the analysis process, it is intended to understand whether an early delivery is the responsibility of the supplier or on the other hand is Bosch's responsibility. To reach that conclusion, it is crucial to eliminate internal causes as the reason for an early delivery. Also, understanding common root causes helps to develop a robust analysis process for early deliveries' cause identification, as there is knowledge about which causes planners need to check.

4.4.2 Developing an early deliveries analysis process

With the main internal causes of early deliveries detected, it is possible to develop an analysis process that would support the use of the BI&A tool and would allow the company to have a standardised way of analysing early deliveries responsibility. Based on the information the BI&A solution presents and the common internal causes, the analysis process is defined and its flowchart is displayed in Figure 25.

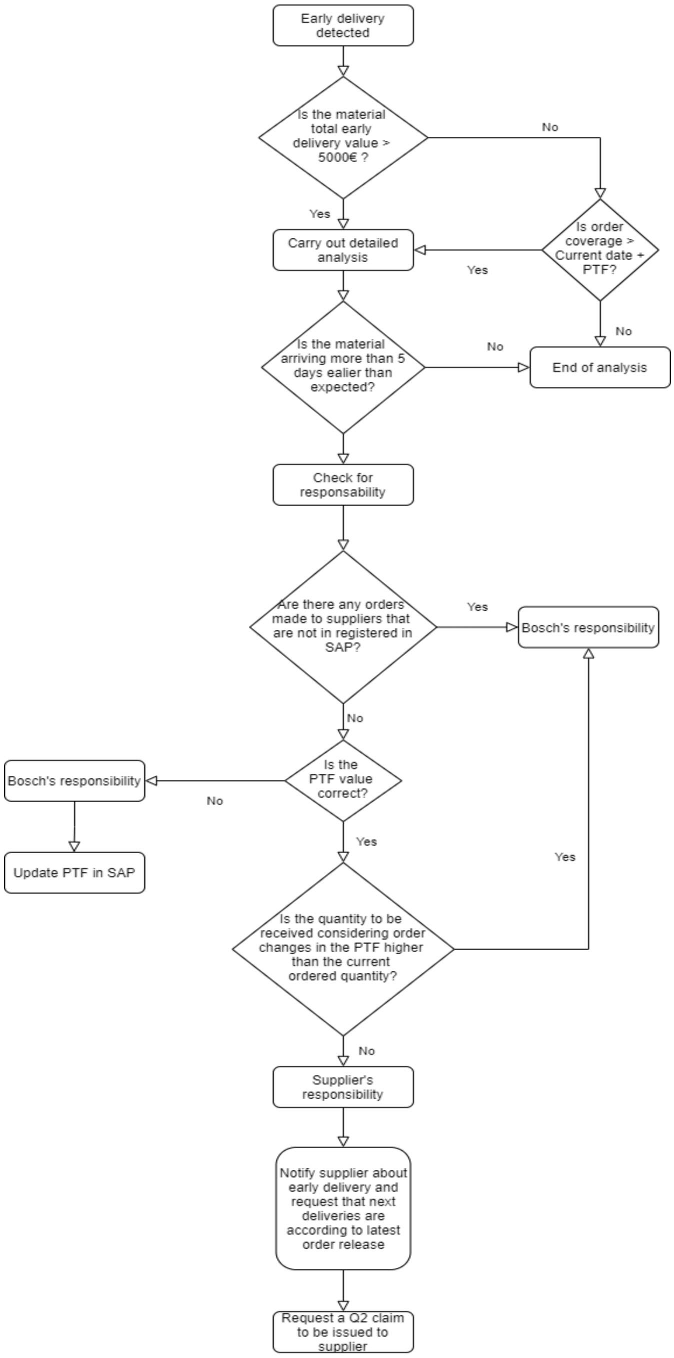


Figure 25 – Early deliveries analysis process flowchart

Planners must check the information in the dashboard daily to check the status of their deliveries and analyse the most critical materials. Nonetheless, a weekly meeting is held by the LOS managers and LOS2 and LOS3 team leaders to detect the most critical materials and request, if needed, for the responsible planner to analyse the material and take action. As seen in Figure 25, the process of analysis of a material that has early deliveries walks planners through different internal causes, allowing them to determine if Bosch is responsible for the early delivery or, otherwise, the supplier is to be born responsible.

Simultaneously, an instructions manual was developed, detailing the functionalities of the dashboard, as well as its use and wherein the dashboard can planners get the information needed. The manual provides help and guidance in the use of the solution, documenting the steps in the dashboard the planner must take to analyse early deliveries. It details the information displayed in each visual. The instruction manual is displayed in Appendix 4 – Dashboard instruction manual. It is important to note that the instruction manual is written in Portuguese, to make it easier for the dashboard users to understand it and avoid any translation problems.

4.4.3 Lessons learned and conclusion

With the creation of the analysis process, there is now a standard to consider when analysing early deliveries. This standard allows the company to determine the responsibility of the early delivery as well as take actions with suppliers in case it is justified. BI&A by itself is not enough, as there needs to be a follow-up on the insights produced by data. Planners claimed sometimes they felt lost, without knowing the next step they should take when analysing an early delivery. Also, the lack of a standard process could mean planners adopted different approaches to early deliveries analysis, which could lead to different outcomes and conclusions. Simultaneously, it also supports the BI&A solution in reducing the time to analyse an early delivery, by detailing the steps a planner must take in the analysis process. Therefore, this analysis process and the instruction manual provide useful guidance to the company in successfully analysing early deliveries, identifying responsibilities and taking actions to improve supplier behaviour, preventing more early deliveries from happening in the future.

4.5 Results of the project

By the end of the project, the results were evaluated to understand the impact the BI&A solution had on early deliveries and the company.

Throughout the project, materials transported by sea were monitored to detect early deliveries, resulting in a total of 148 materials that were signalled as having early deliveries and analysed by LOS planners. From the analyses carried out, a total of 34 Q2 claims were issued to 22 different suppliers. Many of the Q2 claims referred to more than one material with early deliveries, meaning that suppliers received a claim for different early deliveries. Also, 1 training with 1 supplier has been done and more were planned to be scheduled.

It is also important to look at the status of early deliveries of materials in transit transport by sea when the project started and by the end. It is possible to see in Figure 26 that there was a significant reduction in the percentage of materials with early deliveries.

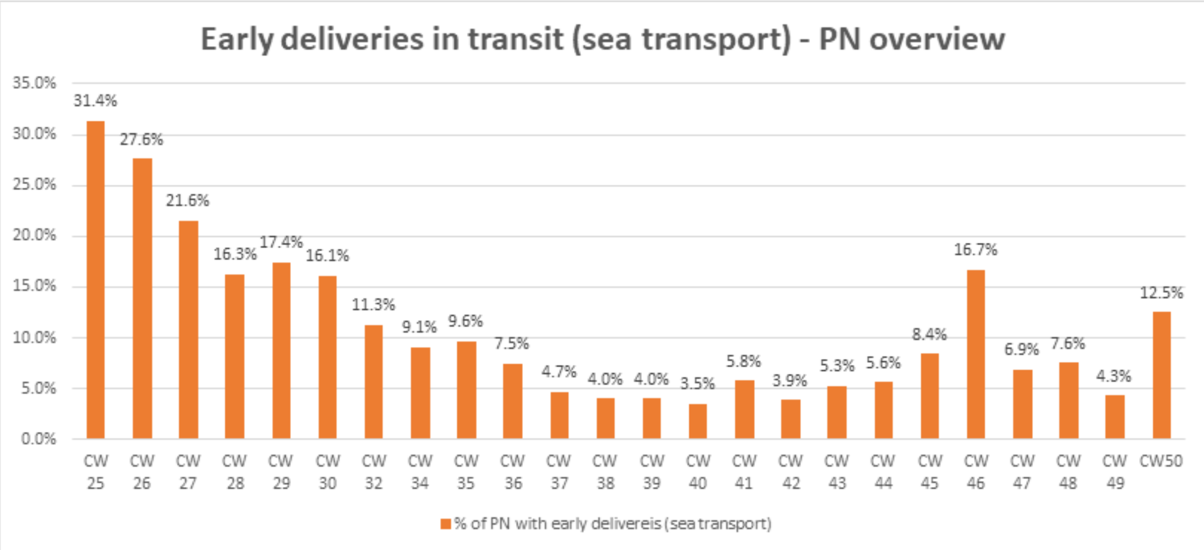


Figure 26 – Percentage of Materials in transit with early deliveries (sea transport)

It is also important to take a look at the value of these early deliveries in transit. The value of the materials is the main indicator since the higher the value of early deliveries, the higher the risk and the cost of unnecessary materials.

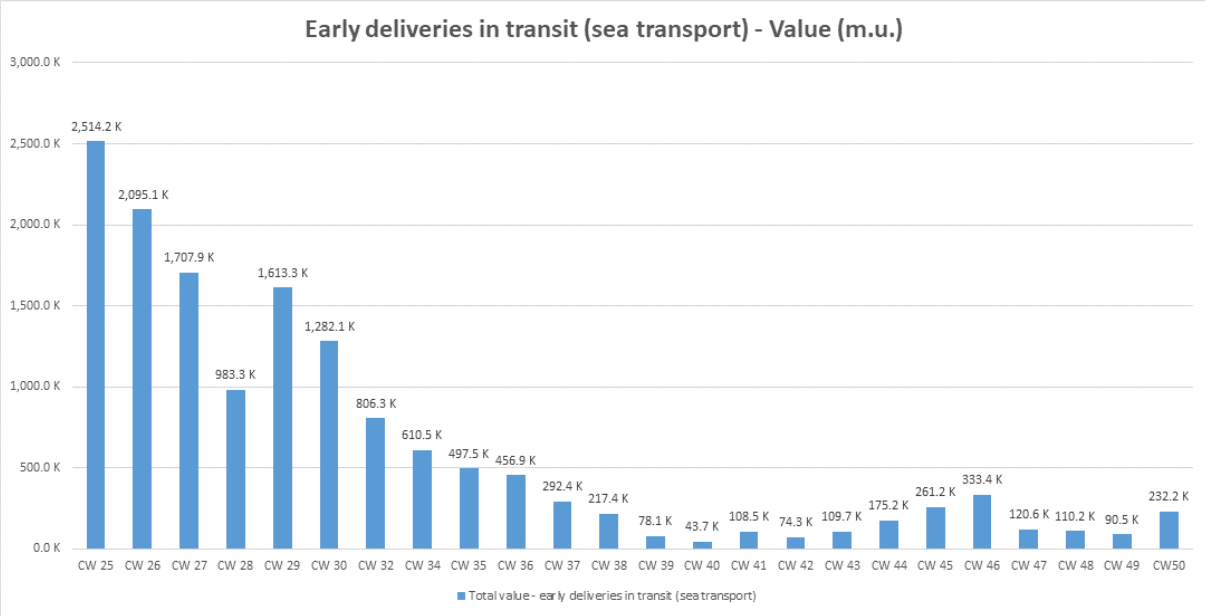


Figure 27 - Value of early deliveries in transit (sea transport)

By looking at Figure 27, in week 25 (when the first EDDR report was implemented), the value of early deliveries was 2,5 million m.u.. This means that 2,5 million m.u. of materials were being sent without any orders from Bosch. In week 50, when the project was concluded, this value was around 232 thousand m.u.. By looking at the data, it is possible to see that from week 37 forward this value was under 300 thousand m.u. except in week 46, where the value was 333 thousand m.u., yet significantly lower than the initial values. With these values, it is possible to see that the value of early deliveries in transit has significantly reduced and is stable.

It is also important to take a look at the early deliveries that arrived at Braga and were stored as pending materials in the LSP's warehouse.

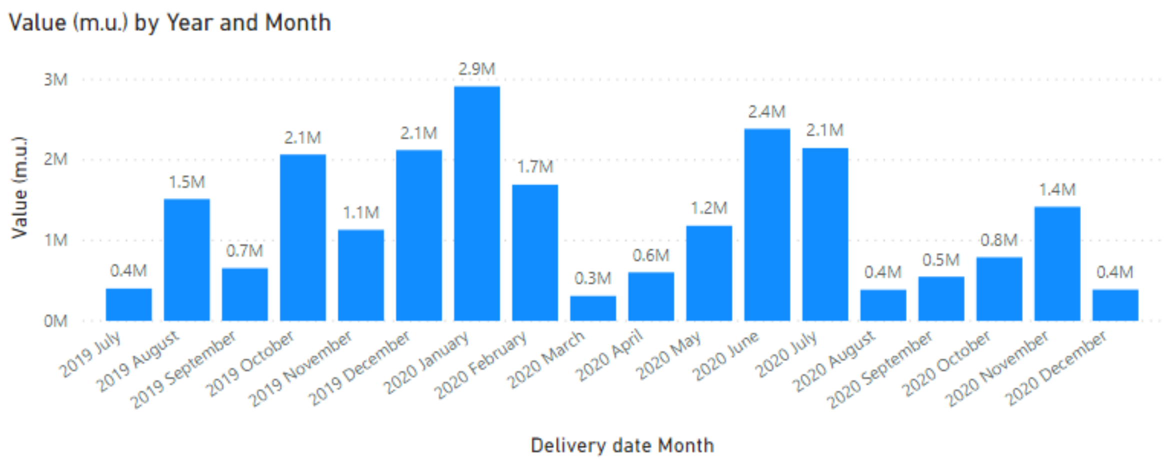


Figure 28 - Value of early deliveries (m.u.) at the LSP from July 2019 to June 2020

As seen in Figure 28, the value of early deliveries that arrived at the LSP's warehouse has reduced in the second semester of 2020. In the second semester of 2020, the monthly average value of early deliveries that arrived at the LSP was 1,32 million m.u.. In the first semester of 2020, this value increased to 1,51 million m.u.. In the second semester of 2020, this value was 0,93 million m.u. (Table 8). This represents a 38% reduction in purchasing costs of unnecessary materials when comparing to the first semester of 2020. This shows there has been a significant reduction in the value of early deliveries, meaning less money is being wasted in buying unnecessary materials.

Table 8 - Value of early deliveries delivered at the LSP's warehouse

	Total value of early deliveries delivered	**Monthly average value of early deliveries**
2nd semester 2019	7,9 million m.u.	1,32 million m.u.
1st semester 2020	9,08 million m.u.	1,52 million m.u.
2nd semester 2020	5,6 million m.u.	0,93 million m.u.

The number of pallets delivered earlier also reduced significantly in the second semester of 2020, as seen in Figure 29.

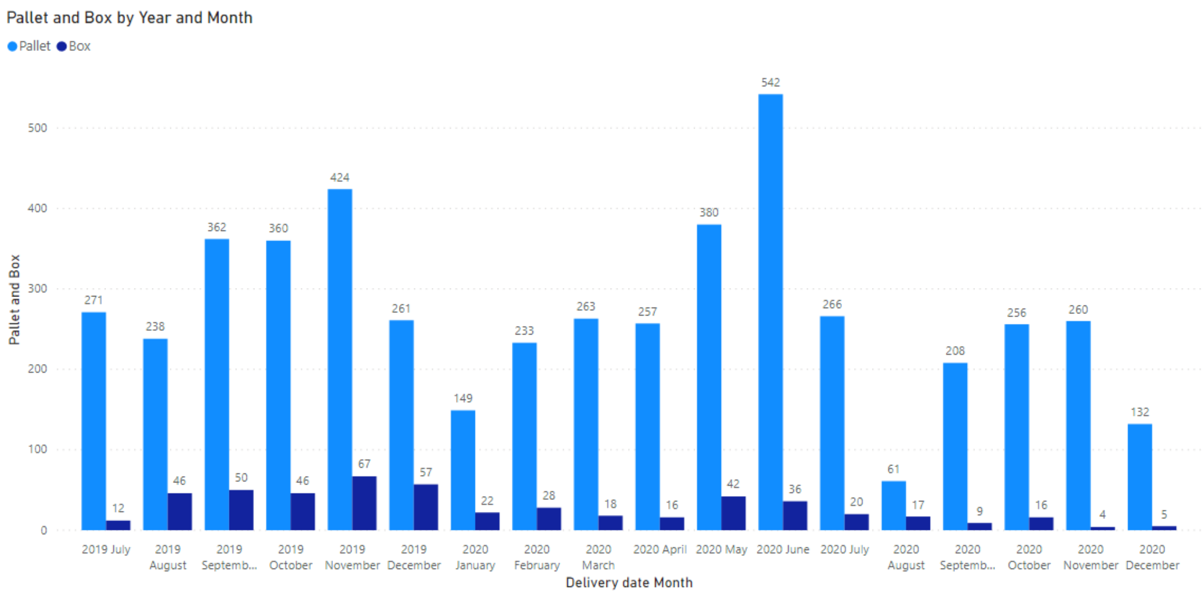


Figure 29 - Number of pallets and boxes delivered earlier than ordered at the LSP

In the second semester of 2020, 1179 pallets were delivered at the LSP earlier than ordered, an average of 6,4 pallets per day. This represents a reduction of 35% when compared to the first semester of 2020, where 1824 pallets of early deliveries arrived, an average of 10 pallets per day. Also, the average number of days materials stayed stored as pending materials (without being registered in SAP) reduced to 8,48 days. With this, it possible to calculate the daily average number of pallets of pending materials stored at the LSP's warehouse, which was 54 pallets in the second semester of 2020, a reduction of 65% when compared to the first semester of 2020 (154 pallets). When compared to the second semester of 2019, there was a 53,8% reduction. As seen in Table 9, warehouse occupation with early deliveries reduced from 2,2 % in the second semester of 2019 and 2,9% in the first semester of 2020 to 1% in the second semester. This value might not seem much, but freeing almost 2% of the warehouse capacity can have a significant impact, especially considering the warehouse is many times being used near to its full capacity, leading to reduced flexibility to deal with increases in demand for raw materials.

Table 9 - Impact of early deliveries on warehouse operations and occupation

	Total number of pallets delivered earlier	Average number of pallets delivered earlier / day	Average days stored as pending material	Average pallets of pending materials stored	Average warehouse occupation rate with early deliveries
2nd semester 2019 (184 days)	1916 pallets	10,4 pallets	11,21 days	117 pallets	2,2%
1st semester 2020 (182 days)	1824 pallets	10 pallets	15,36 days	154 pallets	2,9%
2nd semester 2020 (184 days)	1179 pallets	6,4 pallets	8,48 days	54 pallets	1%

This data shows that the project has positively impacted warehouse operations and occupation. This, in turn, resulted in reduced early deliveries storage and handling costs paid to the LSP by Bosch. As seen in Table 10, the total warehousing costs (storage and handling costs) of early deliveries in the second semester of 2020 were 8 494,22 m.u., a reduction of 47% when compared to the 16 137, 97 of the first semester of 2020.

Table 10 - Early deliveries total warehousing costs

	Total Warehousing Costs (m.u.)
2nd semester 2019	16 251,09 m.u.
1st semester 2020	16 137,97 m.u.
2nd semester 2020	8 494,22 m.u.

Finally, it is important to take a look at the impact of this project and its results on the global supply chain performance of the company.

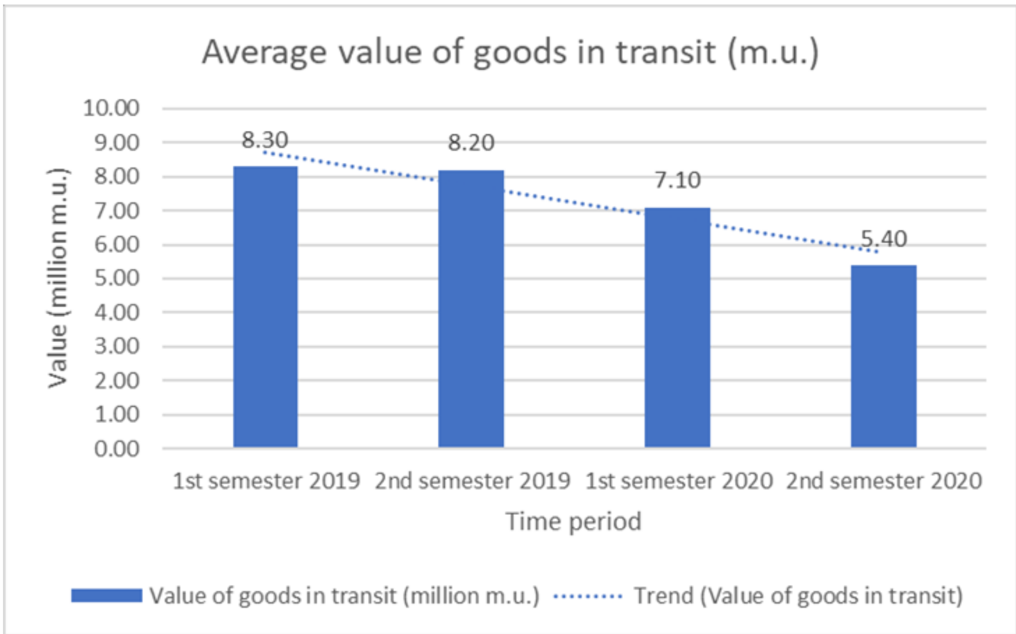


Figure 30 - Value of goods in transit in 2019 and 2020

As seen in Figure 30, the average value of goods (raw materials) in transit has reduced significantly when compared to the prior three semesters. As it is possible to see, the value of goods in transit reduced to 5,4 million m.u., compared to the 7,1 million m.u. of the first semester of 2020, and to the 8,2 and 8,3 million of the second and first semesters of 2019. A reduction of the goods in transit was already expected in 2020 due to the COVID-19 pandemic. However, this effect was only expected in the first semester due to the customers' orders cancellation. Considering this, it is important to look at these results by comparing them to the sales volume. If we weigh the goods in transit value by the sales volume, it is possible to confirm that despite a sales increase in the second semester of 2020 compared to the first semester of 2020, the percentage of goods in transit by sales volumes is still lower, even when compared to 2019 (Figure 31).

Figure 31 - Percentage of goods in transit by sales volume in 2019 and 2020

With a sales increase, it would be expected the value of materials in transit would increase as a result of a higher demand for raw materials. However, there was a reduction in the percentage of goods in transit by the sales volume. As the data shows, on average, the percentage of goods in transit by sales volume has reduced to 5% in the second semester of 2020, lower than in the first semester of the same year. Sales volume reduced significantly in the first semester of 2020 due to the COVID-19 pandemic. However, even by looking at results before the COVID-19 pandemic, it is possible to see that in the first semester of 2019 the percentage of goods in transit by sales volume was 8% and 7% in the second semester of 2019. This shows a 29% reduction of goods in transit value by sales volume in the second semester of 2020 when compared to the same period of 2019.

This in turn has reduced the overall raw materials stocks of the company. As seen in Figure 32, on average, the percentage of stock value by sales volume in the possession of Bosch has reduced in the second semester of 2020, showing a positive impact on stock levels. The stock value by sales volume was 54% in the second semester of 2020, a reduction of 24% when compared to the first semester of 2020 and of 2% when compared to the second semester of 2019.

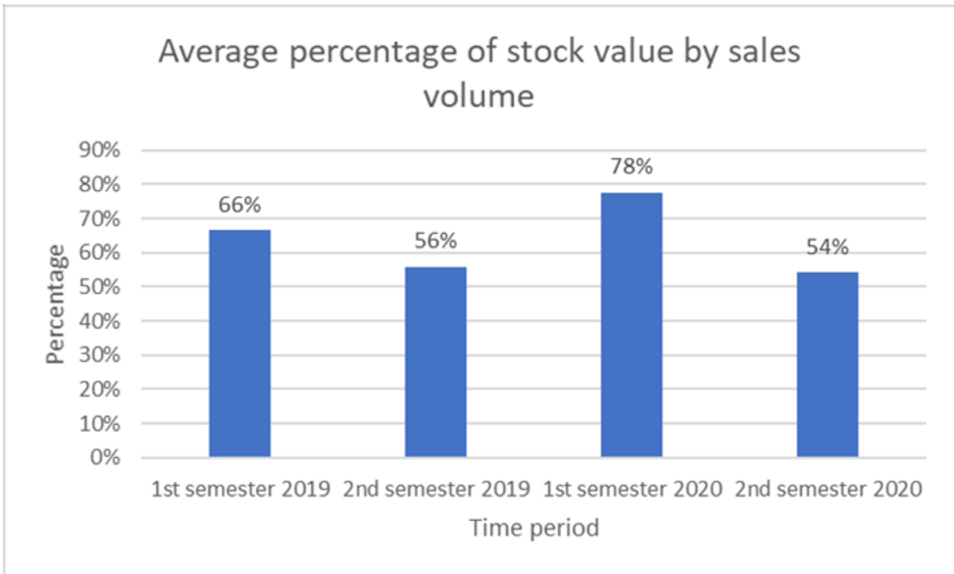


Figure 32 - Percentage of stock value by sales volume in 2019 and 2020

Therefore, it is believed that the project developed has positively impacted Bosch's operations, by reducing early deliveries and the transport of unnecessary materials. This in turn has led to reduced goods in transit, as well as stocks levels. With this, it is shown that the BI&A solution supported by the analysis process has brought significant advantages to the company, achieving extremely satisfactory results. This has led the project to receive attention from the central Logistics Planning team of the AE division, which was positively impressed by the BI&A solution and has expressed interest in expanding its use to the entire AE division.

5. A DESCRIPTIVE ANALYTICS APPROACH TO STUDY SUPPLIER EARLY DELIVERIES AND POTENTIAL RISK FACTORS

With this chapter, it is intended to gain some knowledge on the problem of supplier early deliveries and what affects it. As mentioned before, there is a lack of information and awareness on what are the variables and risk factors that might make a certain material or supplier prone to delivering earlier than ordered (problem 5, as identified in section 3.3.3). The literature fails to mention and study the problem of early deliveries. Therefore, this work presents the opportunity to delve deeper into the problem of early deliveries.

The goal of the study presented is to better understand what can possibly be some of the risk factors that lead suppliers to deliver early than ordered and that might help the company better assess the risk of different suppliers. Historical early deliveries data is collected, as well as data about suppliers, orders and other information considered relevant to the problem. The data is prepared, cleansed and analysed to find trends and patterns in supplier early deliveries performance. With the analyses performed, it is possible to shed some light regarding the early deliveries problem, as well as laying the ground for future research on the topic of suppliers early deliveries, as well as supplier performance as a whole.

5.1 Scope of the study

The initial idea for the study is to study each delivery and identify the ones with early and late deliveries to create an understanding of what affects a delivery and causes a deviation. The idea of studying not only early but also late deliveries is to form a better understanding of how suppliers and deliveries' performance as a whole was impacted. However, some obstacles have been found from the start.

The first obstacle found is the lack of data regarding late deliveries. Late deliveries data is recorded in SAP, through a transaction that assesses delivery performance, or On-Time Delivery (OTD). However, this SAP function is going through some changes, with new parameters and a new method for performance assessment being implemented. These changes have been creating some problems that affect the accuracy of the performance measurement, which in turn affect the available data. The data lacks quality and accuracy and has been considered inappropriate to be analysed. Therefore, it has not been possible to include late deliveries in the study.

The second barrier faced regards early deliveries. As previously mentioned, early deliveries are registered on an excel file. However, deliveries information is registered in SAP. Therefore, there is the need to link an early delivery from the excel file to the delivery registered in SAP, to identify the ones that are early deliveries and the ones that are not. However, this is not possible, since no key allowed to link the data records between the two sources, making it impossible to identify which of the deliveries registered in SAP are actual early deliveries.

Facing these two barriers, it has been decided to study early deliveries in an aggregate form, i.e., study the overall performance of deliveries for a certain material or supplier over a period of time. The initial decision was to study the performance of material for each supplier instead of the overall performance of the suppliers. The idea of studying the performance of a material is to capture some of the dynamics that are unique and differ between different materials. For instance, for the same supplier, two materials might have different performances due to different factors, such as the order variation or project the material is allocated to. If the overall performance of the supplier was to be studied, these dynamics would be captured as data from several materials would be grouped by supplier.

However, after carrying out an initial analysis of the early deliveries of materials, it has been noticed that the dataset is highly unbalanced.

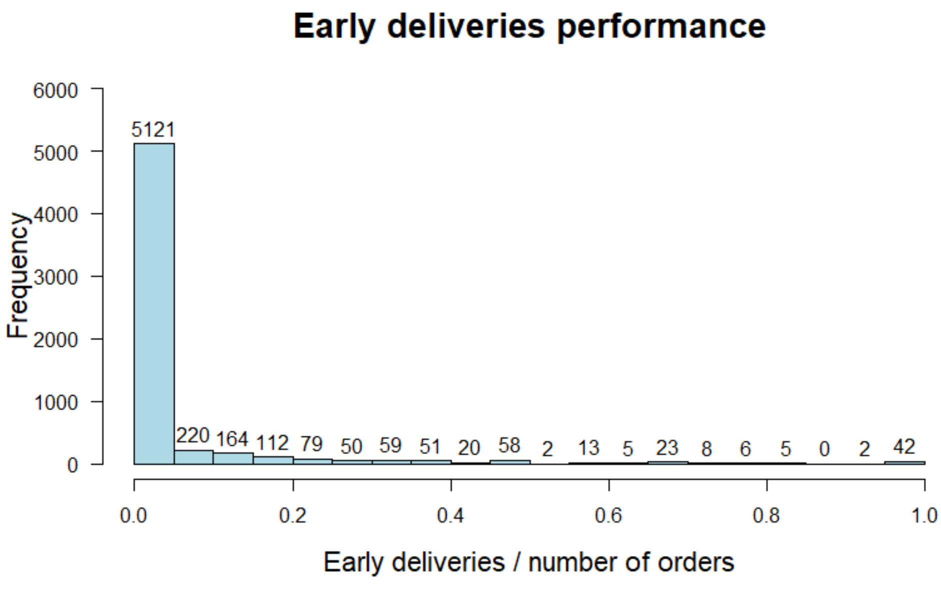


Figure 33 - Distribution of early deliveries performance of materials

As seen in Figure 33, after studying the distribution of early deliveries performance (the number of early deliveries divided by the total number of orders), it has been found that 5121 materials have an early deliveries performance equal to or under 0.05. Of this 5121, 5110 materials did not have any early deliveries, meaning that around 85% of the materials on the dataset have not had any early deliveries.

This imbalance makes the analysis difficult. This is a problem faced in deliveries performance analysis, where datasets tend to be imbalanced (Baryannis, Dani, et al., 2019; Alexandra Brintrup et al., 2020). Hence, attending to the dimensions of our dataset and to avoid some bias in the analyses derived from the introduction of balancing algorithms to cope with this problem (e.g., SMOTE (Chawla et al., 2002)), it has been decided to analyse suppliers performance rather than materials performance.

The distribution of early deliveries performance for suppliers is displayed in Figure 34.

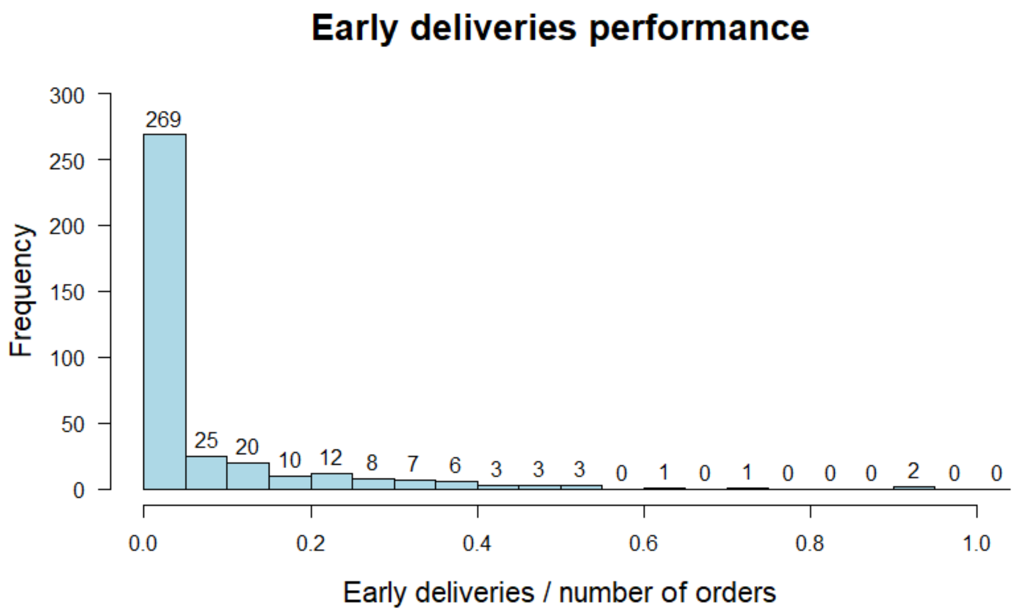


Figure 34 - Distribution of early deliveries performance of suppliers

Figure *34* clearly shows that when we group the data by suppliers, the imbalance is reduced, with 269 suppliers with an early deliveries performance equal to or under 0.05. Of these 269 suppliers, 214 have no early deliveries, which represents around 58% of the suppliers analysed. By analysing performance by supplier, we can reduce the imbalance in data, despite it still being present as seen in the distribution in Figure 34. This imbalance in data is expected as there are many more on-time deliveries than early deliveries. It is also important to account that late deliveries are also not being considered to assess supplier performance, which presents as a limitation of the study, as its inclusion would reduce this imbalance and increase the quality and completeness of the analysis.

5.2 Data requirements and collection

To carry out this study, several risk factors and variables were identified as potentially affecting suppliers performance. These were identified with the experience of the author, built from the BI&A solution project and its integration on the procurement team, as well as by inputs given by experienced process experts that were part of the company. The period chosen for the study was the period between July 2019 and December 2020. This year and a half period was chosen to include in the study a relatively large time horizon that could provide enough data for the study and especially considering that the first semester of 2020 was atypical due to the Covid-19 pandemic. Also, data regarding early deliveries before July 2019 was found to be incomplete and inaccurate and was therefore left out of the study to avoid possibly inaccurate analyses. The variables that were available and collected for the study are displayed in Table 11.

Table 11 - Overview of data identified to perform the analysis

Variable	Description
Vendor	Supplier code
Number of PNs by Value Stream	Number of materials each supplier has allocated to each Value Stream
Number of PNs owned by planners	Number of materials from each supplier owned by each planner
Number of type C PNs	Number of type C materials supplied by each supplier
Number of type B PNs	Number of type B materials supplied by each supplier
Number of type A PNs	Number of type A materials supplied by each supplier
Number of PNs	Total number of materials supplied
PTF	Planning Time Fence of the supplier
Number of delivery windows	Number of delivery windows in a week where a supplier can make its deliveries
Incoterm	Incoterm agreed with the supplier for the delivery process
Ordered quantity value	Total monetary value ordered to a supplier by Bosch
Number of orders	Total number of orders made to a supplier
Monthly average number of orders	Average number of orders sent to a supplier in a month
Number of early deliveries	Number of early deliveries of each supplier in the studied period
Value of early deliveries	Monetary value of early deliveries of each supplier in the studied period
Number of air freights (iStars)	Number of Istars (special air freights) made by each supplier
Value of air freights (iStars) quantities	Value of the materials delivered by Istars (special air freights)
Origin of dispatch (region)	Region from where supplier dispatches deliveries to Bosch
Transport mode	Transport mode used by the supplier to deliver goods to Bosch
Consignment	Indicator of whether supplier operates under consignment with Bosch
Standard deviation of the value ordered monthly	Standard deviation of the monetary value of the monthly orders
Range of the value ordered monthly	Range of the monetary values ordered by Bosch monthly
Early deliveries performance	Number of early deliveries by the total number of orders

With the variables, identified, the next step would be to identify their source and collect them. For this, two main sources were used: data kept in excel files and data stored in SAP (DALI). For the second source, the data gathering process was the same as the one carried out for the BI&A solution, which was presented in section 4.3.1.. In fact, much of the data used was gathered using the same queries, with minor adjustments in filters and fields extracted. Therefore, this process will not once again be illustrated.

5.3 Data cleansing and preparation

With the needed data gathered, the next step is to prepare the data to be analysed. The data is divided into 13 different datasets and the goal is to integrate the data through a series of operations, resulting in a single dataset to be used to perform the analyses. It is rare for data to be in the wanted format and structure to be analysed, as is this case. Therefore, data cleansing and preparation operations were performed by building data workflows using KNIME Analytics Platform[2]. The workflows built for orders and Istars data, as well as some of the operations performed, can be seen in Figure 35. Appendix 5 – Early deliveries data cleansing and preparation (data workflow) shows the entire data workflow and the operations performed to prepare the dataset.

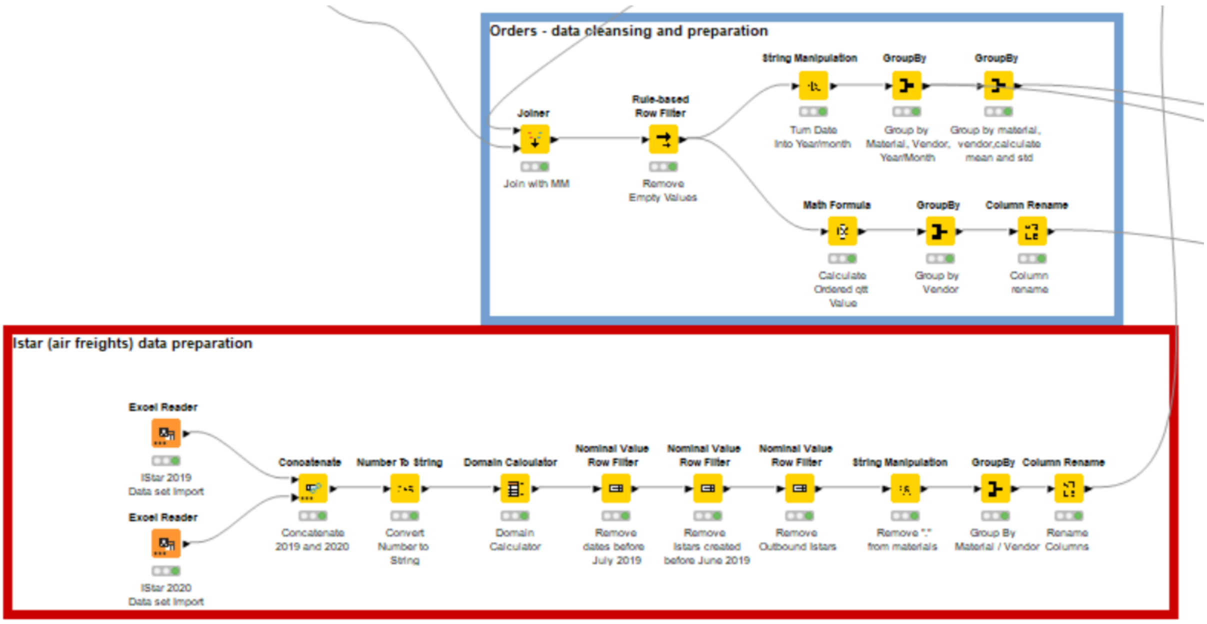


Figure 35 - Data cleansing and preparation workflow for orders dataset and Istars dataset

5.4 Exploratory data analysis – identifying trends in early deliveries

[2] KNIME Analytics Platform - KNIME Analytics Platform is the open source software for creating data science. Intuitive, open, and continuously integrating new developments, KNIME makes understanding data and designing data science workflows and reusable components accessible to everyone (https://www.knime.com/knime-analytics-platform).

With the data ready, the next step is to analyse the variables and attempt to find trends and patterns in the data that can explain the suppliers' early deliveries performance. A total of 370 suppliers were used for the analysis, with the data corresponding to the period between July 2019 and December 2020. To carry out the analyses, the R programming language was used (Appendix 6 – R code used for analysis of early deliveries performance and potential risk factors).

Throughout this section, attention is focused on the development of exploratory data analyses that could raise some interesting insights based on the logistics data under analysis. At this point, it should be emphasized that Exploratory Data Analysis is of the utmost importance to perceive initial statistical patterns and trends in the data that could guide future research actions in the context of predictive analytics. As such, due to the nature of our data, efforts will be concentrated on understanding the data, from a statistical point of view, rather than directly develop predictive models.

5.4.1 Origin, transport mode and PTF

As seen in Figure 36, suppliers who ship their deliveries from out of Europe have the worst performance when it comes to early deliveries. However, it is possible to see that there is a high variation in this performance, with the performance median for these suppliers being close to 0, meaning that 50% of the suppliers from out of Europe have a relatively good performance. Nevertheless, there is still a portion of suppliers with high levels of early deliveries, with the quartile group 3 going up to around 0.20 early deliveries per number of orders, with the upper quartile suppliers reaching scores slightly higher than 0.4. Suppliers shipping from Portugal have very low numbers of early deliveries, while suppliers shipping from Europe (but out of Portugal) also performing better than suppliers from out of Europe, although there are several outliers with high levels of early deliveries between European suppliers. It becomes clear that the origin region from where the supplier is shipping their deliveries might have some influence on early deliveries performance. However, it is important to note that suppliers from Portugal represent a smaller portion of the total number of suppliers of Bosch, as seen in Figure 37.

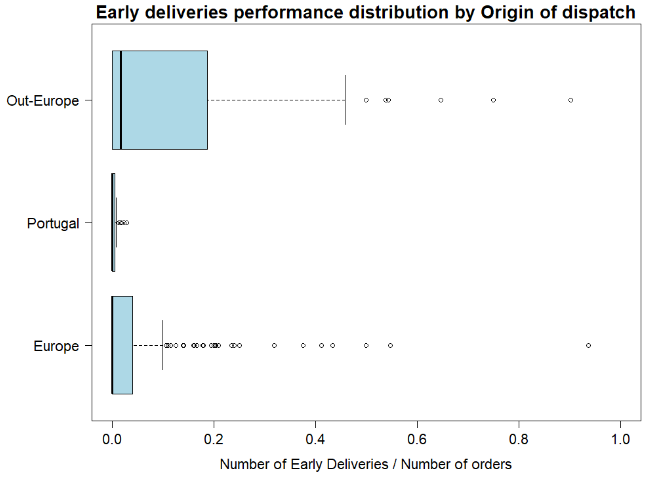


Figure 36 - Boxplot of early deliveries performance by origin of dispatch

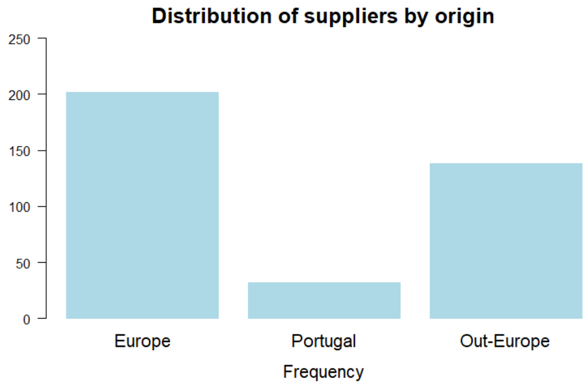


Figure 37 - Distribution of suppliers according to their origin

Transport mode also appears to display a trend in early deliveries performance, as seen in Figure 38. Suppliers who ship their deliveries by sea present the worst levels of early deliveries performance, when compared to transport by land and by air. Suppliers who ship by sea are suppliers who ship from out of Europe, although some of these suppliers ship using air transport. However, sea transport presents a higher median value of early deliveries performance when compared to out of Europe suppliers (displayed in Figure 36), as well as a higher upper quartile and maximum value.

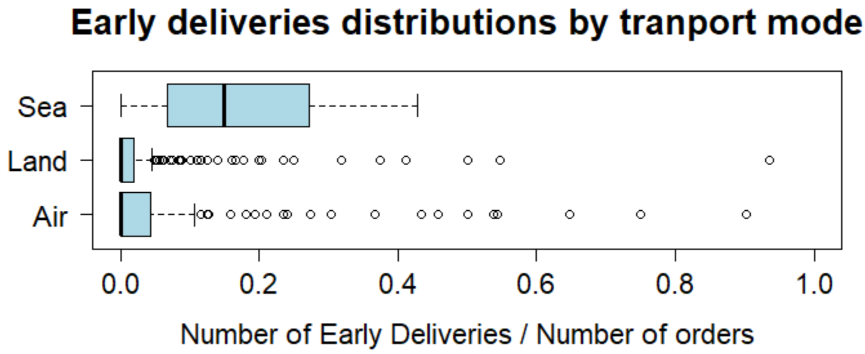


Figure 38 - Boxplot of early deliveries performance by transport mode

This appears to indicate that suppliers from out of Europe and who ship by sea have more early deliveries per number or orders than other suppliers. This idea might find an explanation in the PTF values. The further away the supplier's origin, the longer the time it takes to complete a delivery. Additionally, this time is increased by the transport mode, with sea transport presenting the higher transport times. This means that these suppliers present higher PTFs due to the longer transport times.

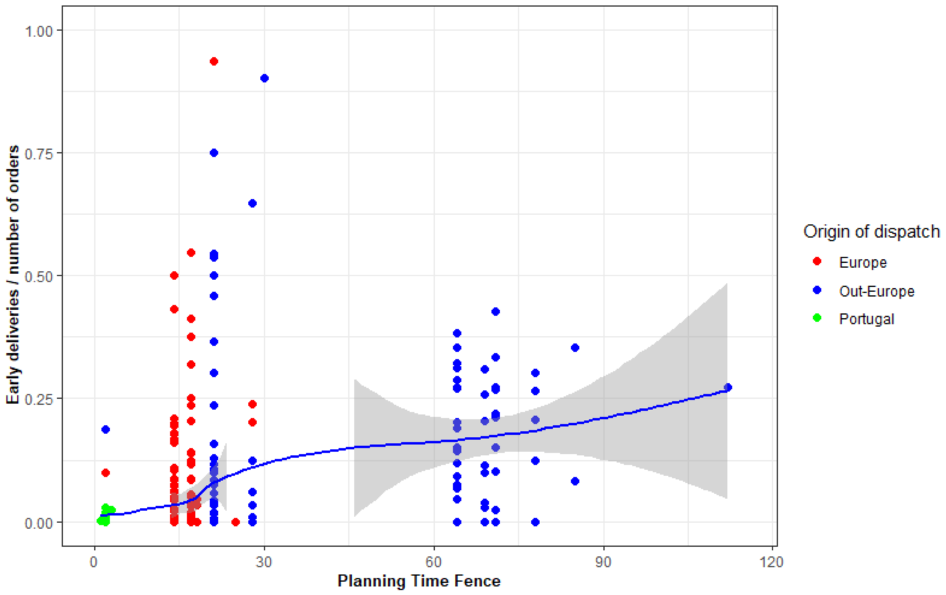


Figure 39 - Plot displaying early deliveries performance vs PTF

Figure 39 displays a clear trend that shows that the higher the PTF, the higher the number of early deliveries per number of orders tends to be. Indeed, the plot shows that there is a greater concentration of suppliers with higher PTFs with more early deliveries per number of orders, meaning that these suppliers tend to perform worse in terms of early deliveries. Suppliers with PTFs under 5 days perform better, while suppliers with PTFs ranging from 15 to 30 days tend to perform worse than suppliers with lower PTFs, but better than suppliers with higher PTFs. Nevertheless, it is possible to see that there are a few outliers with lover PTFs that present high levels of early deliveries per number of orders.

5.4.2 Number of materials

Another trend identified was between early deliveries performance and the number of materials (or PNs) a supplier sells to Bosch. As Figure 40 shows, there is a tendency for the supplier's early deliveries performance to be worse as the number of materials supplied grows. This trend is more marked for smaller numbers of PNs and starts flattening as it grows.

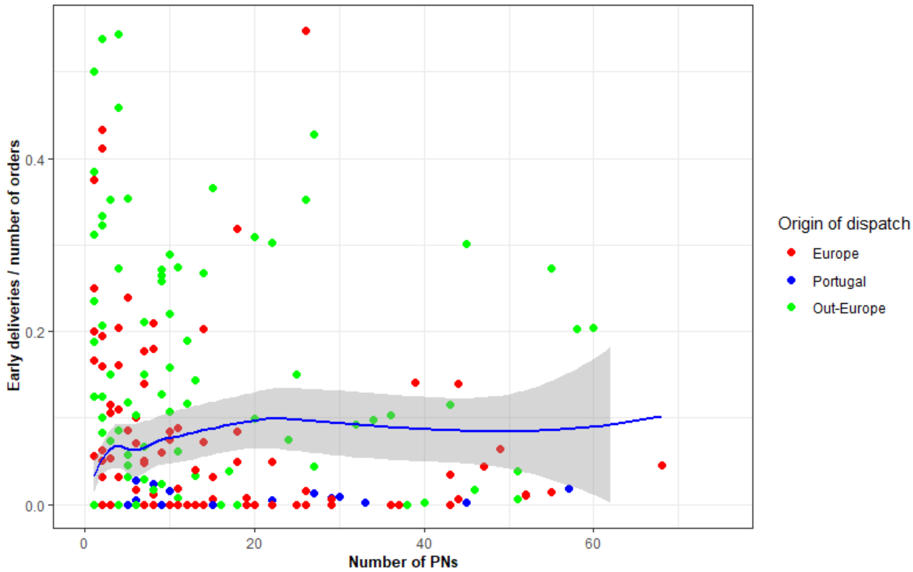


Figure 40 - Plot displaying early deliveries performance vs Number of materials

However, if the analysis is divided by the origin of the suppliers, it is possible to get more insights. As Figure 41 shows, with suppliers from out of Europe, the trend shows that the higher the number of PNs supplied by a supplier, the higher the number of early deliveries per number of orders. For European suppliers, this trend is much less obvious, with a slight increase of early deliveries per number of orders, as the number of PNs grows. For national suppliers, this variable does not seem to have an impact at all as the number of early deliveries is very small. This shows that there could be a relation between the number of materials supplied and the early deliveries performance of the supplier, although this effect appears to be moderated by the origin of the supplier or, possibly, the high PTFs that most of these suppliers have.

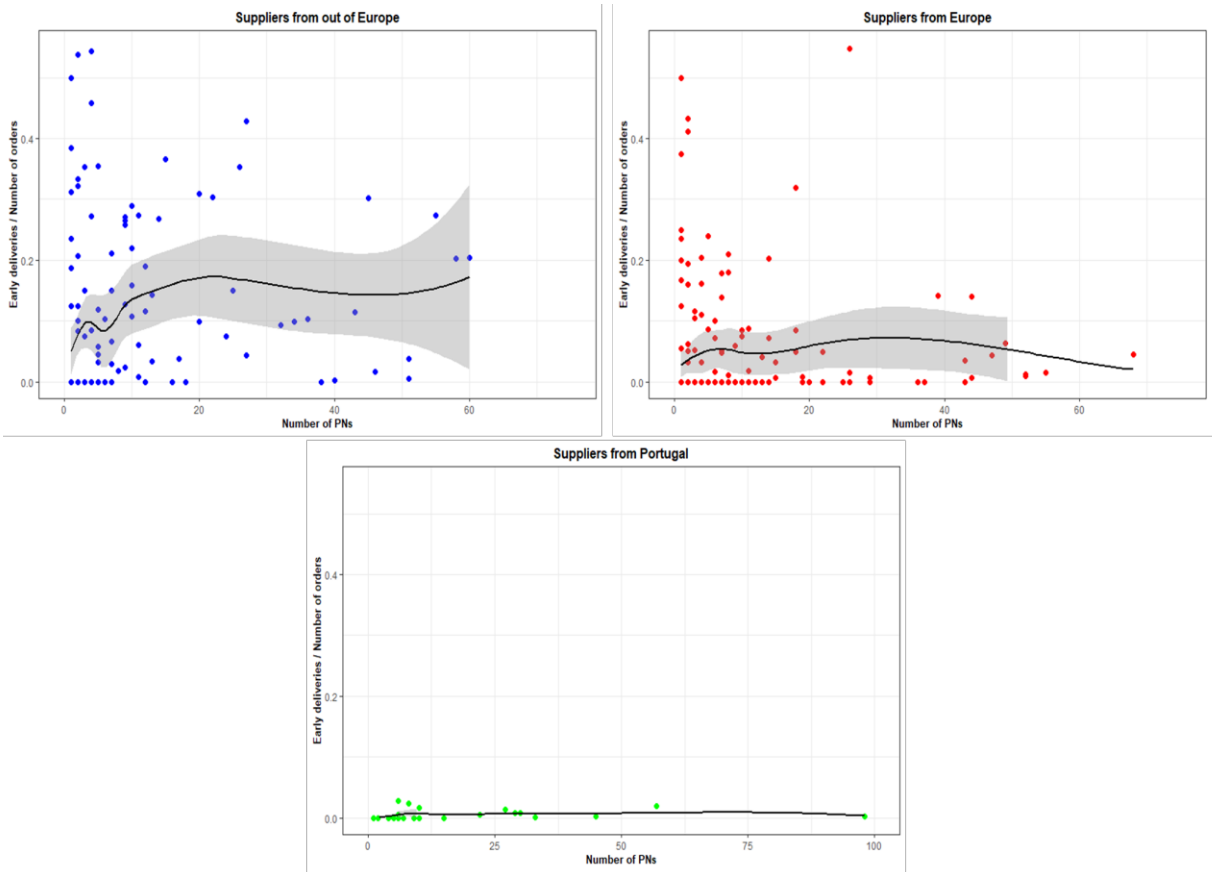


Figure 41 - Plots displaying early deliveries performance vs Number of materials by origin of dispatch

5.4.3 Orders

By analysing the impact of the orders to suppliers, it is also possible to identify some trends that might indicate a possible connection between them and suppliers' performance. As seen in Figure 42, there appears to exist a trend showing that as the average number of monthly orders grows, the number of early deliveries per number of orders appears to increase. However, there is a point where the opposite trend starts (the maximiser), and early deliveries performance improves as the average number of monthly orders increases.

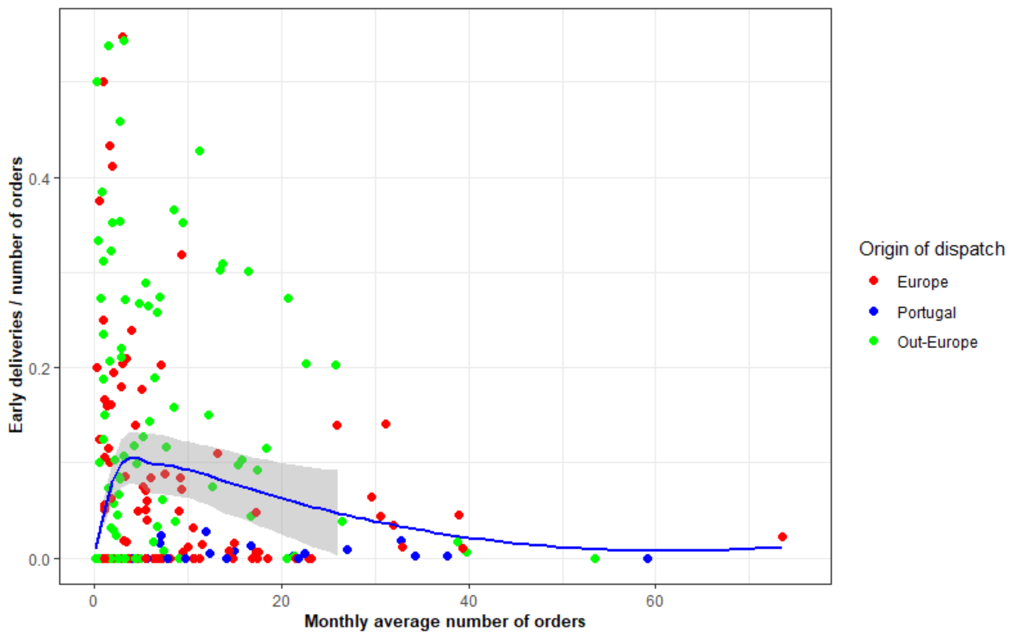


Figure 42 - Plot displaying early deliveries performance vs Average number of monthly orders

When we analyse the data by origin of dispatch (Figure 43), it possible to see that this trend is more marked for out of Europe suppliers, where the maximiser is higher, with an average number of monthly orders higher than 10, while on the plot from Figure 42 this value is smaller than 5. With this information, and by comparing the performance of suppliers from different origins, it is possible to see that suppliers from out of Europe with a higher average number of monthly orders tend to perform worse and have more early deliveries per number of orders than suppliers from Europe and Portugal.

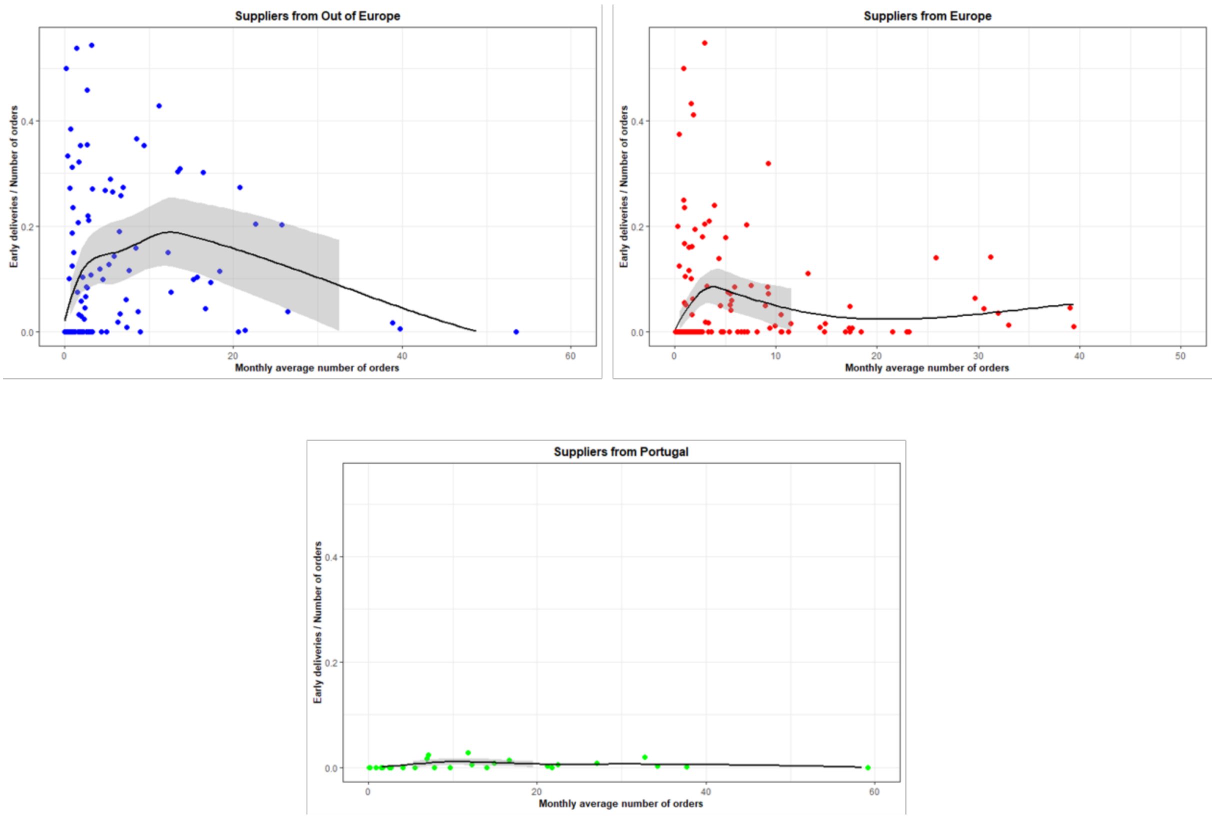


Figure 43 - Plots displaying early deliveries performance vs Average number of monthly orders by origin of dispatch

This trend appears to be supported by another variable, the total ordered value in the analysed period.

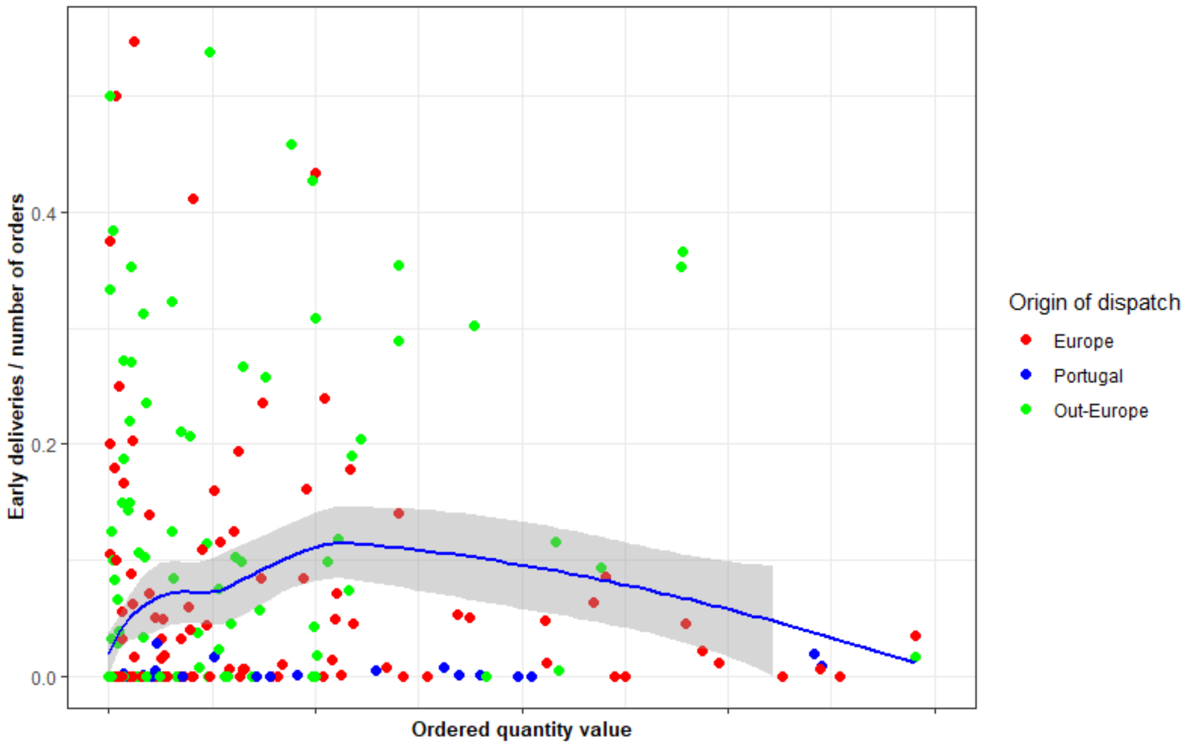


Figure 44 - Plot displaying early deliveries performance vs Total orders monetary value

As seen in Figure 44, the number of early deliveries per number of orders increases as the total order value to suppliers increases, although after a while the trend changes, showing the worst performers appear to be the ones with fewer orders value. Figure 45 shows that this trend is much more marked for suppliers originating from out of Europe, showing that as the total ordered value increases, generally the early deliveries performance is worse. On European suppliers, it is possible to see a curve, showing a positive relationship between the two variables, but after a certain value, this relationship is negative.

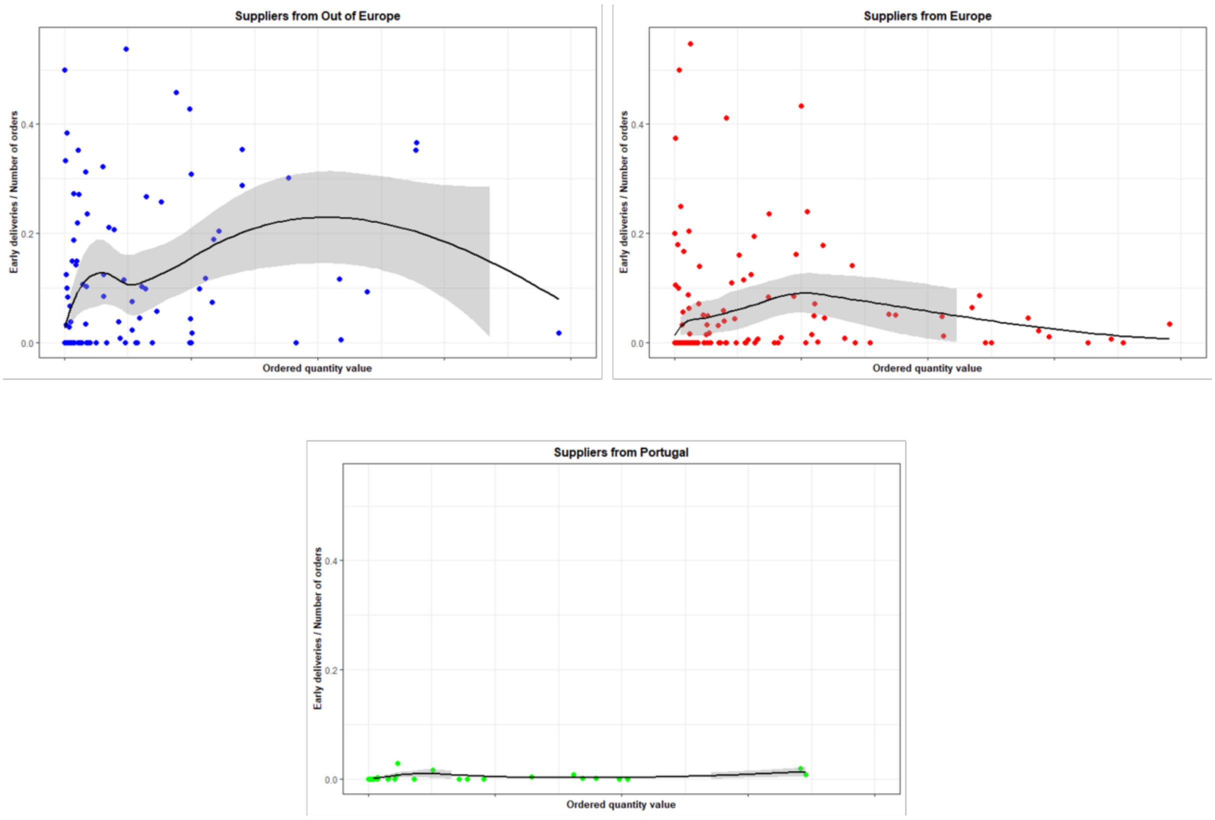


Figure 45 - Plots displaying early deliveries performance vs Total orders monetary value by origin of dispatch

What these plots appear to show is that suppliers with fewer orders and fewer sales to Bosch perform worse than suppliers who have more orders and more sales volume. This can indicate that have more business volume with the company are more committed to successful deliveries since they want to keep an important client with a big volume of sales satisfied. On the contrary, suppliers with a low business volume might be less committed and therefore do not focus as much on achieving on-time deliveries. However, it is important to underline that these are mere possibilities and they need to be further studied with more data and analyses to draw conclusions.

Another variable that reveals a trend is the standard deviation of the value ordered monthly. As seen in Figure 46, generally, as the standard deviation increases, the number of early deliveries per number of orders also increases. This shows that the suppliers with higher variations in monthly order values, tend to perform worse than suppliers who have more steady monthly order values.

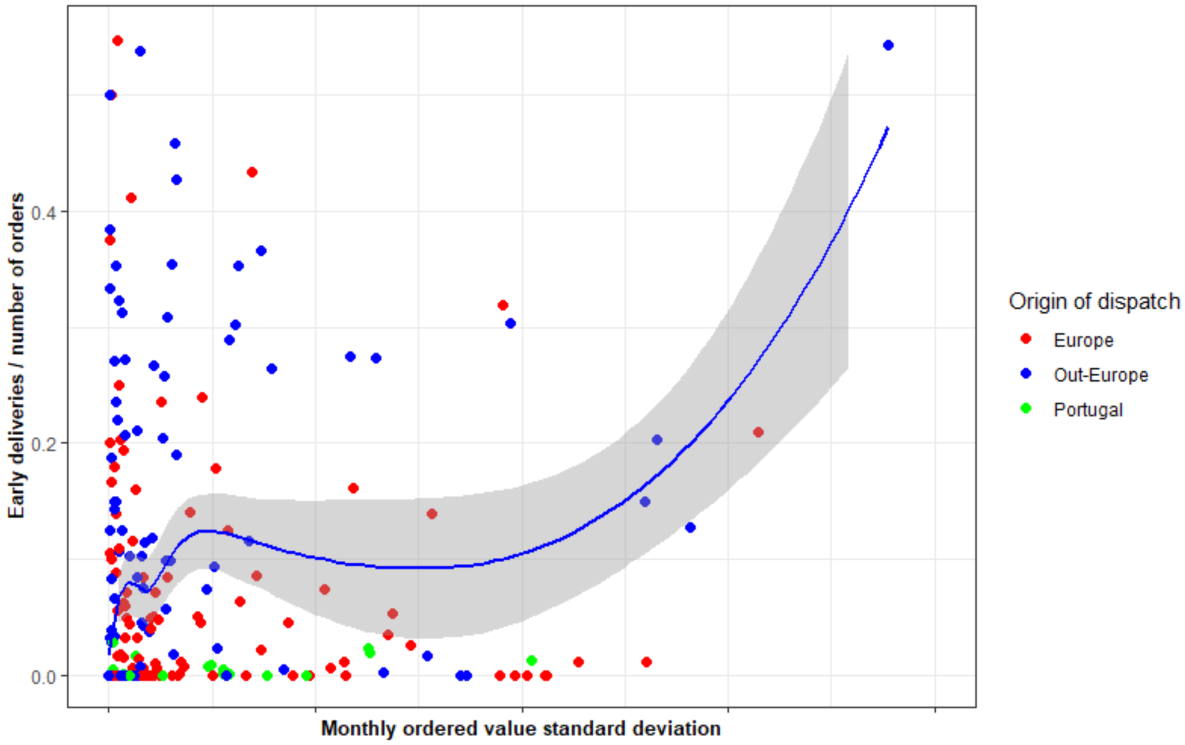


Figure 46 - Plot displaying early deliveries performance vs Standard deviation of the value ordered monthly

Once again, the analysis by origin (Figure 47) shows that this trend is more marked for suppliers from out of Europe, where the early deliveries performance is worse as the standard deviation of the monthly ordered value grows. Generally, European suppliers also display this trend, although the number of early deliveries per number of orders grows in a much smaller proportion as the standard deviation of the monthly ordered value grows. This graph also appears to confirm what the precious analyses showed, that the origin of dispatch of the supplier seems to have a moderating effect, as depending on the origin of the supplier, the different variables affect early deliveries performance differently. This is called an interaction effect (James et al., 2013). Also, as stated before, the origin of the supplier might not be the actual cause for the poor early deliveries performance. This cause could be the PTF, as higher PTFs mean bigger less flexibility to adjust orders to face demand fluctuation, which might lead to order adjustments without suppliers' consent. Also, longer PTFs mean higher transport times, usually by sea, which is highly volatile and subject to transport time variations. However, to confirm these possible relationships, more studies are needed.

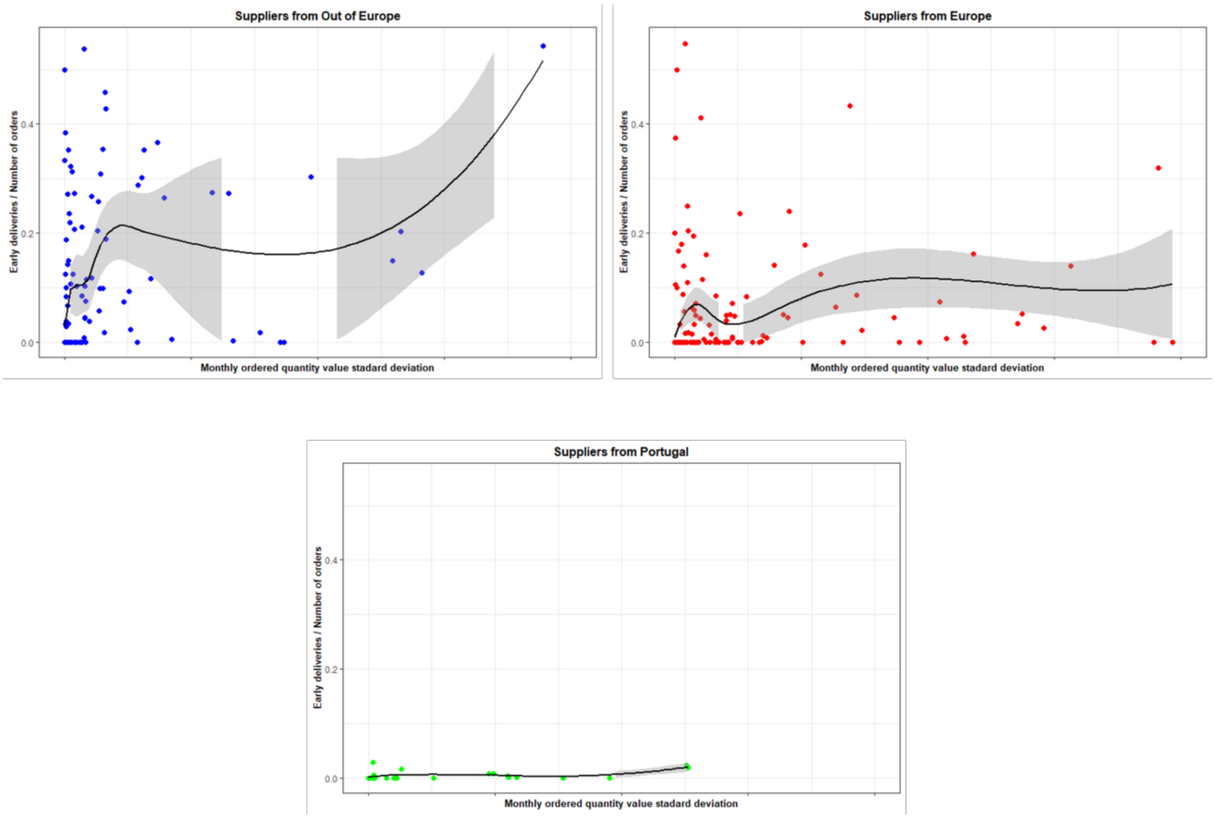


Figure 47 - Plots displaying early deliveries performance vs Standard deviation of the value ordered monthly by origin of dispatch

5.4.4 Air freights (iStars)

Another variable that displays a trend is the number of air freights (iStars) made by Bosch. Air freights are done when the company need a material to be supplied quickly, either due to an unexpected demand increase for the material or a sea transport delay, for example. As Figure 48 shows, there is a trend showing that as the number of air freights done for a certain supplier increases, the number of early deliveries per number of orders also increases. Two possible reasons are thought to explain this potential relationship. The first one has been addressed in section 4.4.1 and it is the fact that when there is a delayed delivery in transit, planners request a second delivery, an air freight, for the same order, meaning there will be two deliveries for the same. However, when an air freight is requested, the second order should be placed in SAP, so that deliveries and order quantities match. If this is not done, when the delayed transport arrives at Braga, there will not be an open order, meaning that the materials will be stored as early deliveries. The second possible explanation is the fact that having more air freights might be an indicator of poor delivery performance by the supplier, as suppliers who fail to deliver accordingly will likely have to do more air freights to make sure the materials arrive on time.

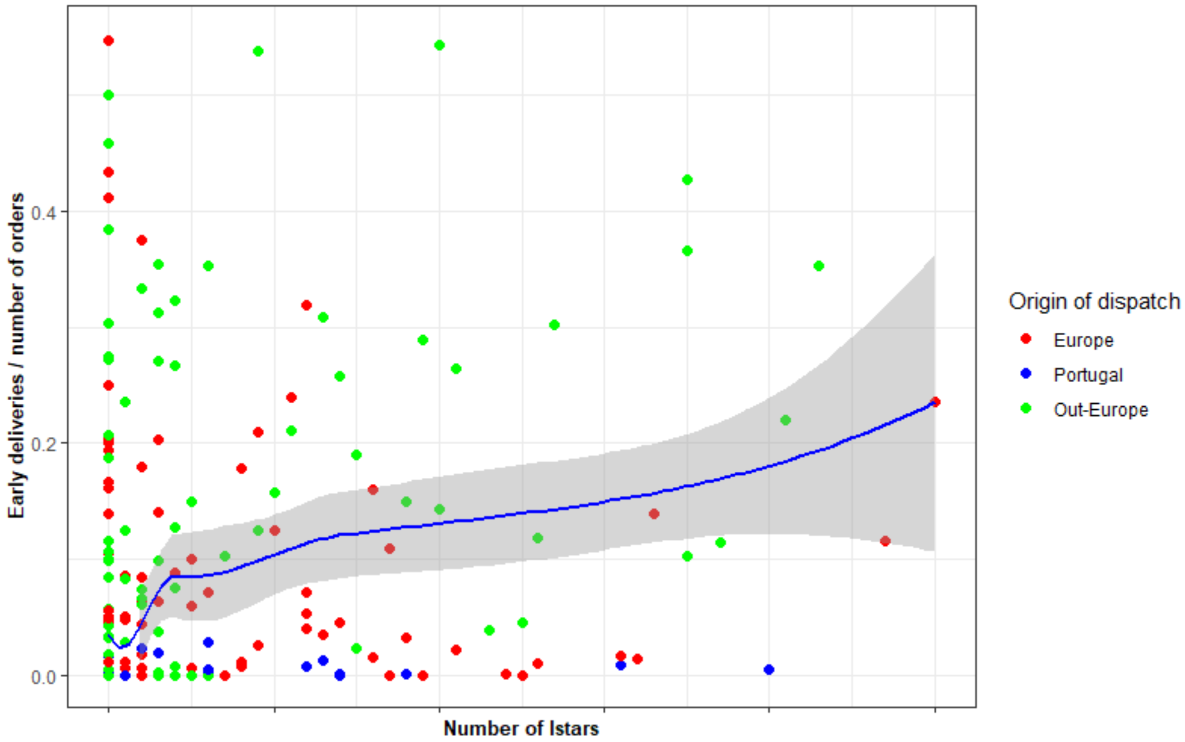


Figure 48 - Plot displaying early deliveries performance vs Number of air freights

If the value of the goods transported by air freights is analysed, it seems to support the idea that more air freights might mean poorer early deliveries performance, as seen in Figure 49.

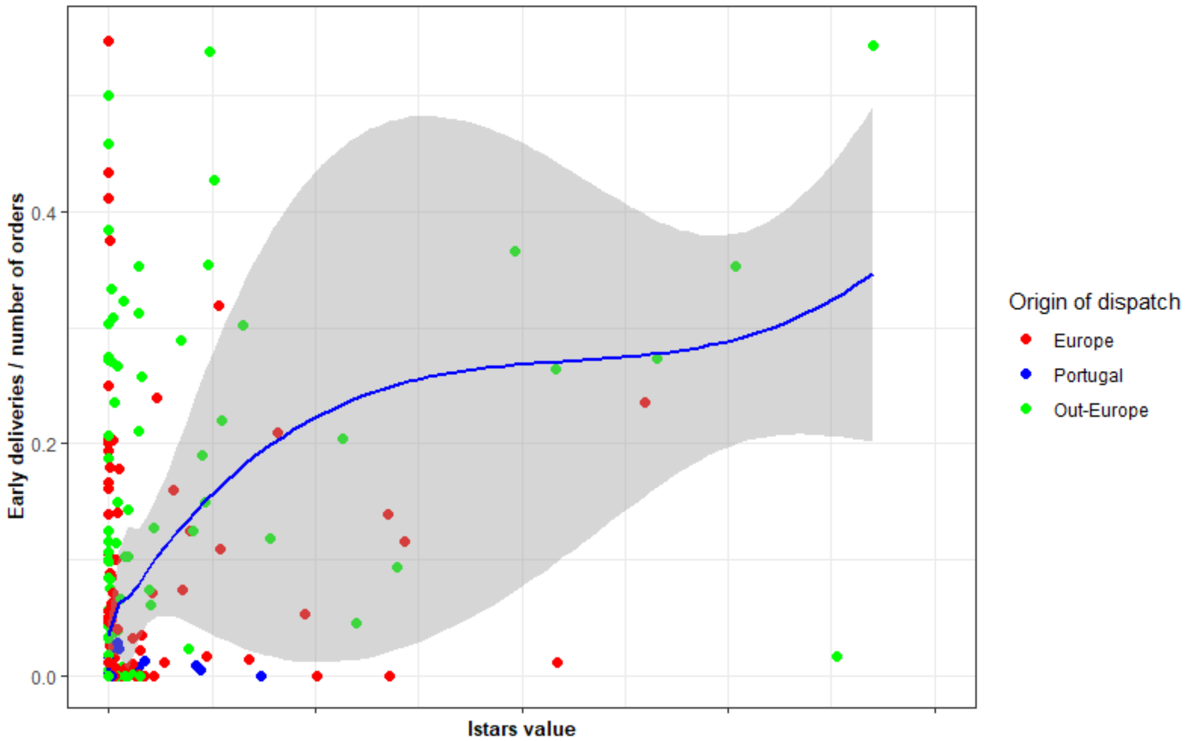


Figure 49 - Plot displaying early deliveries performance vs Value of air freights

With these analyses, it possible to see that suppliers with more air freights tend to have more early deliveries per number of orders, thus showing a potential relationship between these two variables.

5.5 Correlation analysis

To better access the relationship between the variables previously presented and the number of early deliveries per number of orders, a correlation analysis was done. As seen by the plots previously presented, the relationships between the variables are not linear, but rather non-linear. Therefore, Spearman's Correlation Coefficient was used, as it assesses relationships between two variables, whether they are linear or not.

Table 12 - Spearman's correlation coefficient analysis between the different features and early deliveries performance

Variable	Spearman's correlation coefficient
Ordered quantity value	0,527902064
Standard deviation of the value ordered monthly	0,508621291
Value of air freights (Istars) quantities	0,481060894
Number of air freights (Istars)	0,460554174
Average number of monthly orders	0,431033959
Number of PNs	0,406089547
PTF	0,285484729

As seen in Table 12, the correlation analysis confirms what the plots seemed to indicate, that the variables presented some kind of relationship with early deliveries performance. The ordered quantity value and the standard deviation of the value ordered monthly present correlation coefficients higher than 0.5, which are relatively strong and show that these two variables partially explain suppliers' early deliveries performance.

Both the value of air freights quantities and the number of air freights had correlation coefficients close to 0.5, 0.48 and 0.46 respectively, which appears to support the idea that air freights partially explain early deliveries performance. The average number of monthly orders and the number of orders also have relatively strong correlations (although more moderate), of 0.43 and 0.4, respectively.

Lastly, the PTF has a weaker correlation with early deliveries performance, of approximately 0,29. However, this weaker result is explained by the data previously analysed. As displayed in the plot, in Figure 39, the early deliveries performance is highly dispersed for suppliers with the same PTF, meaning that the range of performance for suppliers with the same PTF is very wide, leading to a smaller correlation. However, the plot and trend analysis clearly show a trend that early deliveries performance gets worse as the PTF increases. Therefore, the PTF effect on early deliveries cannot be neglected, as it clearly displays a trend. That is why it is important to combine the different analyses (plot, trend and correlation) to understand the impact different variables have on early deliveries.

5.6 On the use of more advanced models

This section intends to provide a concise overview of how the research actions presented in the present chapter could evolve into the application of more advanced statistical learning techniques. As stated before, due to the nature and structure of the data, it has been preferred to rely on exploratory data analyses as predictive analyses were not suitable for this particular dataset. Nevertheless, it is considered that is it important to raise awareness of this problem by showing some relevant research directions regarding the application of unsupervised and supervised learning approaches towards a better understanding of the core problem of this dissertation.

5.6.1 Unsupervised learning

The analyses carried out provided some insights on some of the variables that affect suppliers' early deliveries performance. However, these analyses have their limitations and more advanced models can and should be used to complement and add more insights that allow more and better conclusions to be withdrawn. Combining more than two variables can help explain better how their combination and interaction explains the number of early deliveries. Unsupervised learning techniques, like clustering models, can help explain the relationship between these variables and suppliers performance, by grouping suppliers in groups (clusters) according to their characteristics and performance. This can help better understand how the performance of different suppliers is influenced by their characteristics and relationship with Bosch (for example, orders behaviour).

With this in mind, for this study, two clustering methods have been deployed in an attempt to discover patterns and group suppliers according to their characteristics and performance. Initially, the k-means clustering algorithm has been deployed and different clusters were generated. However, these clusters are highly irregular. For instance, it is possible to find in the same cluster suppliers with completely different levels of early deliveries performance, ranging from a score of 0 to a score higher than 0.5. This means that the points clusters had very different values, with high distances between points in the cluster, which is not desired, as it is wished to minimise the intra-cluster distances. This shows that the clusters generated included the same cluster suppliers with very different characteristics and performance. To tackle this problem, the k-medians algorithm has been deployed to see if this method achieved better results. However, the performance of the k-medians model was also poor.

Three main reasons can explain this problem. The first is the imbalanced dataset. As explained in section 5.1, the dataset used is highly imbalanced, as it is natural in suppliers/deliveries' performance datasets. This problem is worsened by the second reason, the quality and availability of the data. As mentioned before, the inclusion of late deliveries was not possible due to the unavailability of the data, which would have helped to balance the dataset and would have given more accurate data regarding suppliers' overall performance (and not only early deliveries). Also, the quality of the early deliveries data has been found to have some problems, as there were several mistakes in the data records, that had to be corrected or were not considered for the analysis. The third and final problem is the relatively high number of outliers found in the dataset, which make the analysis of the data difficult. The existence of these outliers can also be a result of the poor quality of the data.

5.6.2 Supervised learning

Supervised learning models can also be interesting to apply to this problem and other similar. In supervised learning, it is wished to fit a model or a function that relates a response variable to the predictors, i.e, it is aimed to predict the response for future observations based on a set of predictors or to understand their relationship (James et al., 2013). In this study, early deliveries performance could be predicted by fitting a model in the explored variables. However, these kinds of advanced models require high accuracy, and to achieve that, data quality and availability is a must, which is not the case. Therefore, these models were tested, as the results of the clustering tests and the prior analyses showed their success was unlikely.

In the future, models such as these have great potential, not only for early deliveries but also for suppliers' overall performance, as it is much more beneficial to study suppliers' performance and behaviour globally. In the presence of reliable and easily available data, models can be deployed to predict suppliers' performance, which might help companies better assess their suppliers and select the best performers. Simultaneously, these models can help understand how the different variables affect and influence suppliers' performance, giving organisations the power to understand what can be improved in their suppliers.

Another potentially beneficial application of these models is the prediction of both early deliveries and late deliveries. These models would allow organisations to identify whether a delivery is going to arrive early, on time or late, giving them the ability to act before the deviations occur and possibly prevent the event or mitigate its consequences. As studied in the literature review, few models like these have been developed. However, none includes early deliveries. Therefore, the inclusion of early deliveries in these studies must be encouraged.

Once again, it is important to underline, that more advanced models such as these can only be successful when there is access to different data sources and that the data used is reliable. Therefore, it is important to guarantee access to quality and reliable data. It is also important to start with more basic analyses, such as the ones presented in this study, to develop knowledge on the problem and analytics maturity. Skipping these steps is not recommended, as it might potentially compromise the success of analytics projects and studies (Arunachalam et al., 2018; Sanders, 2016).

6. DISCUSSION AND CONCLUSIONS

In this chapter, the results of the dissertation are analysed and the main conclusions are presented, as well as their implications. Lastly, some ideas for future work and research directions are proposed in the hope of uncovering new opportunities.

6.1 Critical analysis of the results

The work presented in this dissertation had two main goals. The first was the development of a BI&A solution that allowed the company to detect, monitor and analyse early deliveries. The second was to study what potential factors impact suppliers' early deliveries performance.

Initially, two research questions were presented to guide and support these goals. These were:

- **RQ1:** What is the current status of research and applications of BI&A in the field of supply chain management, more specifically, supply management?
- **RQ2:** Can BI&A help Bosch to detect supplier delivery deviations, improving visibility and reduce early deliveries?
- **RQ3:** Which factors appear to influence Bosch suppliers to send deliveries earlier than expected?

To answer **RQ1**, a thorough literature review was carried out to identify what topics around the application of BI&A in supply chains have been studied and what has research been focusing on (see Chapter 2). A research process was defined and a total of 114 articles were selected from the initial sample and analysed in detail. With this, it was possible to understand what topics have been studied. Different BI&A definitions were presented and a definition of BI&A in supply chains proposed. The benefits and impact of BI&A in supply chains, as well as the barriers faced in its implementation and development, were studied and analysed, according to what has been identified in the literature. Lastly, the existing applications of BI&A to different problems in the field of supply management were presented, detailing the problem they attempt to tackle and the solutions developed. Simultaneously, an overview of the variables used in the literature to assess and understand suppliers and deliveries performance was carried out. The findings of this research allowed answering the first question (**RQ1**), as the gaps were pointed out and topics for future research suggested.

By analysing the early deliveries faced by the company different problems were identified (see Chapter 3). In an attempt to tackle these problems, different solutions were explored (see Chapter 4). In an attempt to stop early deliveries before they leave supplier's facilities, a solution was explored that would allow Bosch to compare the orders and the planned supplier deliveries. However, this solution was considered difficult to implement.

Then, at the first stage, the EDDR was developed to allow the company to detect early deliveries before they arrive at Braga. After the positive results and feedback of implementing this report, a BI&A solution was developed. The solution extracts, prepares and analyses data automatically, presenting the information regarding potential early deliveries to planners. This allows them to identify materials with early deliveries that require monitoring and actions to prevent future deviations. Simultaneously, the report supports planners in analysing the possible cause of the early delivery and determine whether the deviation is Bosch' responsibility or the supplier's. To assist in this responsibility analysis and support the use of the BI&A solution, an analysis process was developed and implemented. The implementation of the mentioned solutions proved to be beneficial, as the results showed a significant reduction in early deliveries (see section 4.5).

The above arguments answer **RQ2**, as the implementation of a BI&A solution helped to detect early deliveries and increase visibility over supplier deliveries, which led to the reduction of early deliveries and the improvement of supply chain operations. However, it is important to underline, that it is believed that BI&A alone did not improve early deliveries. If no follow-up actions were done by the planners on the information presented by the BI&A solution, early deliveries would not have reduced. Thus, it is proposed that the BI&A solution can help detect supplier delivery deviations and, supported by a process and with data-based follow-up actions, can help reduce early deliveries. These findings seem to support the findings of other authors, that suggest that BI&A can lead to improvements in SC performance, but its effect is moderated by the ability of organisations to act on the insights provided by the data (B. Chae et al., 2014; B. K. Chae et al., 2014; B. K. Chae & Olson, 2013; Ravi Srinivasan & Swink, 2018).

Finally, a study was carried out to identify possible risk factors that affect suppliers performance and make them more prone to make early deliveries (see Chapter 5). At the first stage, different variables thought to impact early deliveries performance were identified and collected. Then, a complex data cleansing and preparation process was carried out to create a dataset ready to be analysed. With the data ready, exploratory data analysis and correlation analysis was carried out to identify the variables that appeared to affect early deliveries performance, as well as trends and possible relationships. The study allowed several conclusions to be drawn and different variables were pointed out as displaying some trends and relationships with suppliers early deliveries performance. With the findings presented, it is possible to identify some risk factors that appear to influence suppliers to send early deliveries, thus answering **RQ3**.

6.1.1 Theoretical implications

The work presented developed and presented in this dissertation adds some contributes to the existing literature.

As mentioned in section 2.1, literature has not yet explored the topic of supplier early deliveries. Few works mention this topic and it is not explored in depth. In this dissertation, an initial analysis is carried out on the impact of supplier early deliveries to Bosch. Not only are the risks identified, but whenever possible, they were quantified and supported with numbers. This allows a better understanding of the impact of early deliveries on the company's operations and performance. To the best of the author's knowledge, this is one of the first works, if not the first, to study the topic to this extension. Therefore, it is believed that this work contributes significantly to raising awareness of a little-explored and researched topic. Early deliveries are a topic that must get more attention as they can have a significant impact on organisations, especially considering the challenges and growing complexity of supply chains.

The literature review on the use of BI&A in SCM, more specifically supply management, that has been presented can guide future research. Based on the built base of knowledge and research gaps identified, new research opportunities and projects can be derived.

One gap identified in the literature review was the lack of BI&A applications for supply monitoring. While supplier selection is a widely studied topic, applications of supply and delivery monitoring are still scarce. Therefore, this dissertation contributes to this topic by presenting a BI&A solution for supplier delivery monitoring, proving that these solutions can achieve good results and are beneficial for organisations.

Simultaneously, the use of descriptive analytics and more basic approaches are less common in the literature, when compared to more advanced models, such as predictive and prescriptive analytics (D. Ni et al., 2020; Souza, 2014; Wang et al., 2016). However, more advanced models are difficult to apply, as they require the availability and quality of data, as well as technical knowledge. It is also important to note that BI&A solutions need to fit the organisation and address the problem faced, and many times more basic solutions are the best option (Sanders, 2016). Also, when implementing SCA&I strategies, it important to develop maturity and not jump stages, which means starting with more basic analytical solutions before gaining experience and knowledge to implement more advanced solutions (Arunachalam et al., 2018; Sanders, 2016). Therefore, this work, where a more descriptive-analytical approach is adopted, adds to the existing knowledge by presenting a BI&A solution that achieves goods results by improving SC visibility and operations.

Finally, the study conducted to analyse suppliers' early deliveries performance provides interesting insights on variables that impact suppliers' performance and lead them to deliver early. Literature has some research done on the topic. However, most of the work is focused on variables used to select suppliers, and there is less work to evaluate, understand and predict suppliers' delivery performance. At the same time, the work developed has only been focused on late and on-time deliveries, while early deliveries are never considered. This work contributes to the existing literature by building some knowledge on potential risk factors that affect suppliers' performance and lead to the occurrence of early deliveries. To the best of the author's knowledge, this is the first study that has aimed to unveil variables that influence suppliers' early deliveries. With a new basis, more variables and more studies can use this study as a starting point.

6.1.2 Managerial implications

The work developed in this dissertation also has practical significance not only to the company where the project was carried out but to other organisations.

Previously, Bosch was unable to monitor supplier deliveries and detect early deliveries before they arrived at Braga and was unable to take any follow-up actions. This occurred as data was scattered and was not used for this purpose. With this dissertation, a new BI&A solution was developed that makes use of the existing data, analyses it and generates intelligence and information, giving the company increased visibility over the inbound supply chain, detecting and reacting to early deliveries, which allows them to reduce their occurrence by disciplining suppliers. Also, an analysis process was defined to assist in the use of the solution and to document the steps and actions needed to successfully make use of the intelligence generated. This is of high importance, as failing to support analytical solutions with processes can lead to its failure, as many times organisations have the data and the information, but lack the ability to act on it.

Simultaneously, the study carried out into some variables influencing early deliveries provided some inputs on what are possibly some risk factors that affect suppliers performance. Based on the inputs provided by this analysis and by developing others, the company can identify critical suppliers and their potential problems and risks, enabling the development of strategies and improvement projects that will allow their mitigation. This, in turn, will lead to better and more efficient SC operations.

6.2 Future work and research directions

Naturally, this dissertation cannot address every issue that needs to be studied and improved. Therefore, some proposals for future work and research directions are presented.

Add historical data analysis to the BI&A solution. The BI&A solution developed displays only the current status of early deliveries. This happens because it uses SAP data that is refreshed daily. However, it would be important to add historical early deliveries data, that allows the company to check automatically the evolution of early deliveries and better assess if improvements have been done and define new targets. This could be done by saving the daily or weekly data of the BI&A solution and would require developing an infrastructure to do so. Another option would be to include the excel files where the early deliveries that arrive at the external warehouse and the plant are registered. These are two different files with two different structures. Also, data quality is flawed, therefore there needs to be some work in standardising the data sources, guarantee their quality and a good storage structure.

Update ETA information. Currently, the ETA of deliveries in the dashboard is the ETA indicated on ASNs created by suppliers. However, these ETAs are calculated automatically by SAP considering the ETD and the parameterised transit time. If any unforeseen events occur, that result in delivery delays, these ETAs are not updated by the carrier or by the suppliers. However, it is important to have this information constantly updated. Therefore, it is prosed that the company works to ensure that the carrier and the supplier update this information in SAP as new events occur and ETAs change, to guarantee the most accurate data and, consequently, more informed decision-making.

Include late deliveries data in suppliers performance analysis. In the study carried out to identify the risk factors of early deliveries performance, late deliveries data was not included due to its absence. Therefore, it is important to start working to guarantee that data is available, not only for performance monitoring, but also to study the overall performance of suppliers and deliveries, and what risk factors and variables affect it. This will allow gaining an overview of the overall performance of suppliers.

Collect more data on potential risk factors and develop further analyses with more advanced models. To form a better understanding of early deliveries and the overall supplier performance (assuming that late deliveries data is included), more variables believed to affect deliveries performance should be collected and explored. This includes gathering data about suppliers, such as, the number of workers, number of clients, number of factories and other variables that allow quantifying its dimension and maturity. Also, more internal data should be included, such as the variation of material necessities over time and the variation of orders to suppliers, to understand how this impacts different suppliers and their performance. This will allow the application of more advanced models of suppliers and deliveries risk assessment. Possible applications could be the identification of critical suppliers and their risk factors, which would allow the company to understand what suppliers they should be focusing on for improvements. This could be done for example, by deploying clustering techniques. Another application could be the prediction of delivery deviations, i.e., predict a delivery would arrive early, late or on time. Having the ability to predict if one delivery is arriving on time would give any organisation the ability to act before a deviation occurs, possibly preventing it, or mitigating its effects by taking immediate actions. As seen in the literature review, these applications are still scarce. Organisations are only as good as the supply chains behind them and, in the future, supply chains are only good as the digital technology behind them (Ivanov et al., 2019). Therefore, more research must be done on the application of BI&A techniques to SC problems.

Incorporate the risk analysis on the BI&A solution developed. Currently, the BI&A solution does not include the analyses carried out in the study presented in Chapter 5. However, it is proposed that the company develops more analyses such as those and others that might be developed in the future regarding suppliers' deliveries performance. This would allow the company to have in possession a toll for delivery monitoring, but also delivery and suppliers performance risk assessment.

Create a functionality for analysis of the variation of orders released to suppliers. Analysing the variations of the orders sent to suppliers is a necessity of the company. In this project, it has been attempted to develop this functionality. Despite the BI&A solution allowing to analyse if there were any orders changes inside the PTF as well as carrying out liability analysis, it is not possible to analyse in-depth orders fluctuation, which would enable the detection of the suppliers with more significant order changes. This would allow the company to carry out improvements in their order planning to reduce this fluctuation, which in turn could lead to improved suppliers performance and more efficient SC operations.

Further studies into the supplier early deliveries problem. Supplier early deliveries are still a topic with very little research and awareness. This work contributes significantly to the extant literature by presenting a detailed analysis of this problem. However, more work is needed to fully understand this problem. Therefore, more research is proposed on early deliveries, especially how this issue affects and impacts different organisations across different industries. It is also important to investigate other organisations that have this problem and how they deal with it.

Bibliography

Abdella, G. M., Kucukvar, M., Onat, N. C., Al-Yafay, H. M., & Bulak, M. E. (2020). Sustainability assessment and modeling based on supervised machine learning techniques: The case for food consumption. *Journal of Cleaner Production*, *251*, 119661. https://doi.org/10.1016/j.jclepro.2019.119661

Afify, A. A., Dimov, S. S., Nairn, M., Valeva, V., & Shukla, V. (2007). Data mining: A tool for detecting cyclical disturbances in supply networks. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, *221*(12), 1771–1785. https://doi.org/10.1243/09544054JEM879

Altintas, N., & Trick, M. (2014). A data mining approach to forecast behavior. *Annals of Operations Research*, *216*(1), 3–22. https://doi.org/10.1007/s10479-012-1236-9

Aqlan, F. (2017). Dynamic clustering of inventory parts to enhance warehouse management. *European Journal of Industrial Engineering*, *11*(4), 469–485. https://doi.org/10.1504/EJIE.2017.086184

Arunachalam, D., Kumar, N., & Kawalek, J. P. (2018). Understanding big data analytics capabilities in supply chain management: Unravelling the issues, challenges and implications for practice. *Transportation Research Part E: Logistics and Transportation Review*, *114*, 416–436. https://doi.org/10.1016/j.tre.2017.04.001

Bala, P. K. (2012). Improving inventory performance with clustering based demand forecasts. *Journal of Modelling in Management*, *7*(1), 23–37. https://doi.org/10.1108/17465661211208794

Balster, A., Hansen, O., Friedrich, H., & Ludwig, A. (2020). An ETA Prediction Model for Intermodal Transport Networks Based on Machine Learning. *Business and Information Systems Engineering*, *62*(5), 403–416. https://doi.org/10.1007/s12599-020-00653-0

Barbosa, M. W., Vicente, A. de la C., Ladeira, M. B., & de Oliveira, M. P. V. (2018). Managing supply chain resources with Big Data Analytics: a systematic review. *International Journal of Logistics Research and Applications*, *21*(3), 177–200. https://doi.org/10.1080/13675567.2017.1369501

Baryannis, G., Dani, S., & Antoniou, G. (2019). Predicting supply chain risks using machine learning: The trade-off between performance and interpretability. *Future Generation Computer Systems*, *101*, 993–1004. https://doi.org/10.1016/j.future.2019.07.059

Baryannis, G., Validi, S., Dani, S., & Antoniou, G. (2019). Supply chain risk management and artificial intelligence: state of the art and future research directions. *International Journal of Production Research*, *57*(7), 2179–2202. https://doi.org/10.1080/00207543.2018.1530476

Baykasoğlu, A., & Gölcük, İ. (2019). A dynamic multiple attribute decision making model with learning of fuzzy cognitive maps. *Computers and Industrial Engineering*, *135*(August 2018), 1063–1076. https://doi.org/10.1016/j.cie.2019.06.032

Bhattacharya, A., Kumar, S. A., Tiwari, M. K., & Talluri, S. (2014). An intermodal freight transport system for optimal supply chain logistics. *Transportation Research Part C: Emerging Technologies*, *38*, 73–84. https://doi.org/10.1016/j.trc.2013.10.012

Bloomberg. (2017, July 14). *Fined for Arriving Early? Wal-Mart Puts Its Suppliers on Notice | IndustryWeek*. https://www.industryweek.com/supply-chain/article/22022636/fined-for-arriving-early-walmart-puts-its-suppliers-on-notice

Bosch. (2020). *Internal Documents*.

Boyle, M. (2017, July 12). *Wal-Mart Will Punish Its Suppliers for Delivering Early - Bloomberg*. Bloomberg Businessweek. https://www.bloomberg.com/news/articles/2017-07-12/fined-for-arriving-early-wal-mart-puts-its-suppliers-on-notice

Brintrup, A., Wichmann, P., Woodall, P., McFarlane, D., Nicks, E., & Krechel, W. (2018). Predicting

Hidden Links in Supply Networks. *Complexity*, *2018*. https://doi.org/10.1155/2018/9104387
Brintrup, Alexandra, Pak, J., Ratiney, D., Pearce, T., Wichmann, P., Woodall, P., & McFarlane, D. (2020). Supply chain data analytics for predicting supplier disruptions: a case study in complex asset manufacturing. *International Journal of Production Research*, *58*(11), 3330–3341. https://doi.org/10.1080/00207543.2019.1685705
Carbonneau, R., Laframboise, K., & Vahidov, R. (2008). Application of machine learning techniques for supply chain demand forecasting. *European Journal of Operational Research*, *184*(3), 1140–1154. https://doi.org/10.1016/j.ejor.2006.12.004
Carvalho, J. C. de. (2017). *Logística e Gestão da Cadeia de Abastecimento*.
Cavalcante, I. M., Frazzon, E. M., Forcellini, F. A., & Ivanov, D. (2019). A supervised machine learning approach to data-driven simulation of resilient supplier selection in digital manufacturing. *International Journal of Information Management*, *49*(March), 86–97. https://doi.org/10.1016/j.ijinfomgt.2019.03.004
Chae, B. K., & Olson, D. L. (2013). Business analytics for supply chain: A dynamic-capabilities framework. *International Journal of Information Technology and Decision Making*, *12*(1), 9–26. https://doi.org/10.1142/S0219622013500016
Chae, B. K., Olson, D., & Sheu, C. (2014). The impact of supply chain analytics on operational performance: A resource-based view. *International Journal of Production Research*, *52*(16), 4695–4710. https://doi.org/10.1080/00207543.2013.861616
Chae, B., Yang, C., Olson, D., & Sheu, C. (2014). The impact of advanced analytics and data accuracy on operational performance: A contingent resource based theory (RBT) perspective. *Decision Support Systems*, *59*(1), 119–126. https://doi.org/10.1016/j.dss.2013.10.012
Chavez, R., Yu, W., Jacobs, M. A., & Feng, M. (2017). Data-driven supply chains, manufacturing capability and customer satisfaction. *Production Planning and Control*, *28*(11–12), 906–918. https://doi.org/10.1080/09537287.2017.1336788
Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). SMOTE: synthetic minority over-sampling technique. *Journal of Artificial Intelligence Research*, *16*, 321–357.
Chehbi-Gamoura, S., Derrouiche, R., Damand, D., & Barth, M. (2019). Insights from big Data Analytics in supply chain management: an all-inclusive literature review using the SCOR model. *Production Planning and Control*.
Chen, D. Q., Preston, D. S., & Swink, M. (2015). How the use of big data analytics affects value creation in supply chain management. *Journal of Management Information Systems*, *32*(4), 4–39. https://doi.org/10.1080/07421222.2015.1138364
Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS Quarterly: Management Information Systems*, *36*(4), 1165–1188.
Chen, M. C., Huang, C. L., Chen, K. Y., & Wu, H. P. (2005). Aggregation of orders in distribution centers using data mining. *Expert Systems with Applications*, *28*(3), 453–460. https://doi.org/10.1016/j.eswa.2004.12.006
Chen, M. C., & Wu, H. P. (2005). An association-based clustering approach to order batching considering customer demand patterns. *Omega*, *33*(4), 333–343. https://doi.org/10.1016/j.omega.2004.05.003
Chen, Y. S., Chen, C. H., & Lai, C. J. (2012). Extracting performance rules of suppliers in the manufacturing industry: An empirical study. *Journal of Intelligent Manufacturing*, *23*(5), 2037–2045. https://doi.org/10.1007/s10845-011-0530-8
Cheng, Y., Peng, J., Gu, X., Zhang, X., Liu, W., Zhou, Z., Yang, Y., & Huang, Z. (2020). An intelligent supplier evaluation model based on data-driven support vector regression in global supply chain. *Computers and Industrial Engineering*, *139*(April 2019). https://doi.org/10.1016/j.cie.2019.04.047

Cheng, Y., Peng, J., Zhou, Z., Gu, X., & Liu, W. (2017). A Hybrid DEA-Adaboost Model in Supplier Selection for Fuzzy Variable and Multiple Objectives. *IFAC-PapersOnLine*, *50*(1), 12255–12260. https://doi.org/10.1016/j.ifacol.2017.08.2038

Chi, H. M., Ersoy, O. K., Moskowitz, H., & Ward, J. (2007). Modeling and optimizing a vendor managed replenishment system using machine learning and genetic algorithms. *European Journal of Operational Research*, *180*(1), 174–193. https://doi.org/10.1016/j.ejor.2006.03.040

Chou, D. C., Bindu Tripuramallu, H., & Chou, A. Y. (2005). BI and ERP integration. *Information Management & Computer Security*, *13*(5), 340–349. https://doi.org/10.1108/09685220510627241

Choy, K. L., Tan, K. H., & Chan, F. T. S. (2007). Design of an intelligent supplier knowledge management system - An integrative approach. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, *221*(2), 195–211. https://doi.org/10.1243/09544054JEM627

Council of Supply Chain Management Professionals (CSCMP). (2013). *SCM Definitions and Glossary of Terms*. https://cscmp.org/CSCMP/Educate/SCM_Definitions_and_Glossary_of_Terms.aspx

Coyle, J. J., Ruamsook, K., & Symon, E. J. (2016). Weatherproofing supply chains: Enable intelligent preparedness with data analytics. *Transportation Journal*, *55*(2), 190–207. https://doi.org/10.1353/tnp.2016.0011

Cui, R., Gallino, S., Moreno, A., & Zhang, D. J. (2018). The Operational Value of Social Media Information. *Production and Operations Management*, *27*(10), 1749–1769. https://doi.org/10.1111/poms.12707

Delen, D., Erraguntla, M., Mayer, R. J., & Wu, C. N. (2011). Better management of blood supply-chain with GIS-based analytics. *Annals of Operations Research*, *185*(1), 181–193. https://doi.org/10.1007/s10479-009-0616-2

Er Kara, M., Oktay Fırat, S. Ü., & Ghadge, A. (2020). A data mining-based framework for supply chain risk management. *Computers and Industrial Engineering*, *139*(December 2018), 105570. https://doi.org/10.1016/j.cie.2018.12.017

Fahimnia, B., Sarkis, J., & Davarzani, H. (2015). Green supply chain management: A review and bibliometric analysis. *International Journal of Production Economics*, *162*, 101–114. https://doi.org/10.1016/j.ijpe.2015.01.003

Flynn, B. B., Huo, B., & Zhao, X. (2010). The impact of supply chain integration on performance: A contingency and configuration approach. *Journal of Operations Management*, *28*(1), 58–71. https://doi.org/10.1016/j.jom.2009.06.001

Geng, X., & Liu, Q. (2015). A hybrid service supplier selection approach based on variable precision rough set and VIKOR for developing product service system. *International Journal of Computer Integrated Manufacturing*, *28*(10), 1063–1076. https://doi.org/10.1080/0951192X.2014.959058

Golpîra, H. (2018). A novel Multiple Attribute Decision Making approach based on interval data using U2P-Miner algorithm. *Data and Knowledge Engineering*, *115*(June 2017), 116–128. https://doi.org/10.1016/j.datak.2018.03.001

Govindan, K., Cheng, T. C. E., Mishra, N., & Shukla, N. (2018). Big data analytics and application for logistics and supply chain management. *Transportation Research Part E: Logistics and Transportation Review*, *114*(March), 343–349. https://doi.org/10.1016/j.tre.2018.03.011

Gudfinnsson, K., Strand, M., & Berndtsson, M. (2015). Analyzing business intelligence maturity. *Journal of Decision Systems*, *24*(1), 37–54. https://doi.org/10.1080/12460125.2015.994287

Guiffrida, A. L., & Nagi, R. (2006). Cost characterizations of supply chain delivery performance. *International Journal of Production Economics*, *102*(1), 22–36. https://doi.org/10.1016/j.ijpe.2005.01.015

Ha, S. H., & Krishnan, R. (2008). A hybrid approach to supplier selection for the maintenance of a competitive supply chain. *Expert Systems with Applications*, *34*(2), 1303–1311. https://doi.org/10.1016/j.eswa.2006.12.008

Hahn, G. J., & Packowski, J. (2015). A perspective on applications of in-memory analytics in supply chain management. *Decision Support Systems*, *76*, 45–52. https://doi.org/10.1016/j.dss.2015.01.003

Handfield, R., Jeong, S., & Choi, T. (2019). Emerging procurement technology: data analytics and cognitive analytics. *International Journal of Physical Distribution and Logistics Management*, *49*(10), 972–1002. https://doi.org/10.1108/IJPDLM-11-2017-0348

Hazen, B. T., Boone, C. A., Ezell, J. D., & Jones-Farmer, L. A. (2014). Data quality for data science, predictive analytics, and big data in supply chain management: An introduction to the problem and suggestions for research and applications. *International Journal of Production Economics*, *154*, 72–80. https://doi.org/10.1016/j.ijpe.2014.04.018

Hazen, B. T., Skipper, J. B., Boone, C. A., & Hill, R. R. (2018). Back in business: operations research in support of big data analytics for operations and supply chain management. *Annals of Operations Research*, *270*(1–2), 201–211. https://doi.org/10.1007/s10479-016-2226-0

Hazen, B. T., Skipper, J. B., Ezell, J. D., & Boone, C. A. (2016). Big data and predictive analytics for supply chain sustainability: A theory-driven research agenda. *Computers and Industrial Engineering*, *101*, 592–598. https://doi.org/10.1016/j.cie.2016.06.030

Hosseini, S., & Khaled, A. Al. (2019). A hybrid ensemble and AHP approach for resilient supplier selection. *Journal of Intelligent Manufacturing*, *30*(1), 207–228. https://doi.org/10.1007/s10845-016-1241-y

Huber, J., Gossmann, A., & Stuckenschmidt, H. (2017). Cluster-based hierarchical demand forecasting for perishable goods. *Expert Systems with Applications*, *76*, 140–151. https://doi.org/10.1016/j.eswa.2017.01.022

Ijadi Maghsoodi, A., Kavian, A., Khalilzadeh, M., & Brauers, W. K. M. (2018). CLUS-MCDA: A novel framework based on cluster analysis and multiple criteria decision theory in a supplier selection problem. *Computers and Industrial Engineering*, *118*(March), 409–422. https://doi.org/10.1016/j.cie.2018.03.011

International Chamber of Commerce. (2020). *Incoterms® 2020 - ICC - International Chamber of Commerce*. https://iccwbo.org/resources-for-business/incoterms-rules/incoterms-2020/

Ivanov, D., Dolgui, A., & Sokolov, B. (2019). The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. *International Journal of Production Research*, *57*(3), 829–846. https://doi.org/10.1080/00207543.2018.1488086

Jain, R., Singh, A. R., Yadav, H. C., & Mishra, P. K. (2014). Using data mining synergies for evaluating criteria at pre-qualification stage of supplier selection. *Journal of Intelligent Manufacturing*, *25*(1), 165–175. https://doi.org/10.1007/s10845-012-0684-z

Jain, V., Wadhwa, S., & Deshmukh, S. G. (2007). Supplier selection using fuzzy association rules mining approach. *International Journal of Production Research*, *45*(6), 1323–1353. https://doi.org/10.1080/00207540600665836

Jain, Vipul, Benyoucef, L., & Deshmukh, S. G. (2008). A new approach for evaluating agility in supply chains using Fuzzy Association Rules Mining. *Engineering Applications of Artificial Intelligence*, *21*(3), 367–385. https://doi.org/10.1016/j.engappai.2007.07.004

Jain, Vipul, Wadhwa, S., & Deshmukh, S. G. (2009). Select supplier-related issues in modelling a dynamic supply chain: Potential, challenges and direction for future research. *International Journal of Production Research*, *47*(11), 3013–3039. https://doi.org/10.1080/00207540701769958

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An Introduction to Statistical Learning - with Applications in R*. Springer. https://www.springer.com/gp/book/9781461471370%0Ahttp://www.springer.com/us/book/9781461471370

Jeble, S., Dubey, R., Childe, S. J., Papadopoulos, T., Roubaud, D., & Prakash, A. (2018). Impact of big data and predictive analytics capability on supply chain sustainability. *International Journal of Logistics Management*, *29*(2), 513–538. https://doi.org/10.1108/IJLM-05-2017-0134

Kandananond, K. (2012). A comparison of various forecasting methods for autocorrelated time series. *International Journal of Engineering Business Management*, *4*(1), 1–6. https://doi.org/10.5772/51088

Khalid, W., & Herbert-Hansen, Z. N. L. (2018). Using k-means clustering in international location decision. *Journal of Global Operations and Strategic Sourcing*, *11*(3), 274–300. https://doi.org/10.1108/JGOSS-11-2017-0056

Lau, H. C. W., Ho, G. T. S., Zhao, Y., & Chung, N. S. H. (2009). Development of a process mining system for supporting knowledge discovery in a supply chain network. *International Journal of Production Economics*, *122*(1), 176–187. https://doi.org/10.1016/j.ijpe.2009.05.014

Lau, R. Y. K., Zhang, W., & Xu, W. (2018). Parallel Aspect-Oriented Sentiment Analysis for Sales Forecasting with Big Data. *Production and Operations Management*, *27*(10), 1775–1794. https://doi.org/10.1111/poms.12737

Lee, B. K., Zhou, R., de Souza, R., & Park, J. (2016). Data-driven risk measurement of firm-to-firm relationships in a supply chain. *International Journal of Production Economics*, *180*, 148–157. https://doi.org/10.1016/j.ijpe.2016.07.025

Lee, C. K. H. (2017). A GA-based optimisation model for big data analytics supporting anticipatory shipping in Retail 4.0. *International Journal of Production Research*, *55*(2), 593–605. https://doi.org/10.1080/00207543.2016.1221162

Lee, C. Y., & Chien, C. F. (2014). Stochastic programming for vendor portfolio selection and order allocation under delivery uncertainty. *OR Spectrum*, *36*(3), 761–797. https://doi.org/10.1007/s00291-013-0342-7

Li, G. D., Yamaguchi, D., & Nagai, M. (2007). Application of grey-based rough decision-making approach to suppliers selection. *Journal of Modelling in Management*, *2*(2), 131–142. https://doi.org/10.1108/17465660710763416

Li, G. D., Yamaguchi, D., & Nagai, M. (2008). A grey-based rough decision-making approach to supplier selection. *International Journal of Advanced Manufacturing Technology*, *36*(9–10), 1032–1040. https://doi.org/10.1007/s00170-006-0910-y

Li, S., Ragu-Nathan, B., Ragu-Nathan, T. S., & Subba Rao, S. (2006). The impact of supply chain management practices on competitive advantage and organizational performance. *Omega*, *34*(2), 107–124. https://doi.org/10.1016/j.omega.2004.08.002

Li, Y., Kramer, M. R., Beulens, A. J. M., & Van Der Vorst, J. G. A. J. (2010). A framework for early warning and proactive control systems in food supply chain networks. *Computers in Industry*, *61*(9), 852–862. https://doi.org/10.1016/j.compind.2010.07.010

Liao, S. H., Chen, C. M., & Wu, C. H. (2008). Mining customer knowledge for product line and brand extension in retailing. *Expert Systems with Applications*, *34*(3), 1763–1776. https://doi.org/10.1016/j.eswa.2007.01.036

Lin, R. H., Chuang, C. L., Liou, J. J. H., & Wu, G. D. (2009). An integrated method for finding key suppliers in SCM. *Expert Systems with Applications*, *36*(3 PART 2), 6461–6465. https://doi.org/10.1016/j.eswa.2008.07.078

Liou, J. J. H., Chuang, Y. C., Zavadskas, E. K., & Tzeng, G. H. (2019). Data-driven hybrid multiple attribute decision-making model for green supplier evaluation and performance improvement. *Journal of Cleaner Production*, *241*, 118321. https://doi.org/10.1016/j.jclepro.2019.118321

Mani, V., Delgado, C., Hazen, B. T., & Patel, P. (2017). Mitigating supply chain risk via sustainability using big data analytics: Evidence from the manufacturing supply chain. *Sustainability (Switzerland)*, *9*(4). https://doi.org/10.3390/su9040608

McKevitt, J. (2017, July 12). *Walmart will fine suppliers for late, early deliveries in push for inventory control | Supply Chain Dive*. Supply Chain Dive. https://www.supplychaindive.com/news/Walmart-supplier-fine-logistics-delivery-OTIF-risk/446948/
Meyer, A., Sejdovic, S., Glock, K., Bender, M., Kleiner, N., & Riemer, D. (2018). A disruption management system for automotive inbound networks: concepts and challenges. *EURO Journal on Transportation and Logistics*, *7*(1), 25–56. https://doi.org/10.1007/s13676-017-0108-5
MH&L Staff. (2017, July 13). *Walmart Suppliers Will Be Fined for Both Early and Late Deliveries | Material Handling and Logistics*. Material Handling & Logistics (MH&L). https://www.mhlnews.com/global-supply-chain/article/22054435/walmart-suppliers-will-be-fined-for-both-early-and-late-deliveries
Mishra, D., Gunasekaran, A., Papadopoulos, T., & Childe, S. J. (2018). Big Data and supply chain management: a review and bibliometric analysis. *Annals of Operations Research*, *270*(1–2), 313–336. https://doi.org/10.1007/s10479-016-2236-y
Moktadir, M. A., Ali, S. M., Paul, S. K., & Shukla, N. (2019). Barriers to big data analytics in manufacturing supply chains: A case study from Bangladesh. *Computers and Industrial Engineering*, *128*(April 2018), 1063–1075. https://doi.org/10.1016/j.cie.2018.04.013
Murray, P. W., Agard, B., & Barajas, M. A. (2015). Forecasting supply chain demand by clustering customers. *IFAC-PapersOnLine*, *28*(3), 1834–1839. https://doi.org/10.1016/j.ifacol.2015.06.353
Murray, P. W., Agard, B., & Barajas, M. A. (2018). Forecast of individual customer's demand from a large and noisy dataset. *Computers and Industrial Engineering*, *118*(February), 33–43. https://doi.org/10.1016/j.cie.2018.02.007
Nguyen, T., ZHOU, L., Spiegler, V., Ieromonachou, P., & Lin, Y. (2018). Big data analytics in supply chain management: A state-of-the-art literature review. *Computers and Operations Research*, *98*, 254–264. https://doi.org/10.1016/j.cor.2017.07.004
Ni, D., Xiao, Z., & Lim, M. K. (2020). A systematic review of the research trends of machine learning in supply chain management. *International Journal of Machine Learning and Cybernetics*, *11*(7), 1463–1482. https://doi.org/10.1007/s13042-019-01050-0
Ni, M., Xu, X., & Deng, S. (2007). Extended QFD and data-mining-based methods for supplier selection in mass customization. *International Journal of Computer Integrated Manufacturing*, *20*(2–3), 280–291. https://doi.org/10.1080/09511920601150651
Oliveira, M. P. V. de, & Handfield, R. (2019). Analytical foundations for development of real-time supply chain capabilities. *International Journal of Production Research*, *57*(5), 1571–1589. https://doi.org/10.1080/00207543.2018.1493240
Oliveira, M. P. V. De, McCormack, K., & Trkman, P. (2012). Business analytics in supply chains - The contingent effect of business process maturity. *Expert Systems with Applications*, *39*(5), 5488–5498. https://doi.org/10.1016/j.eswa.2011.11.073
Pandolph, S. (2017, July 17). *Walmart will start fining its suppliers for early and late deliveries*. Insider. https://www.businessinsider.com/walmart-fining-suppliers-early-late-deliveries-2017-7
Papadopoulos, T., Gunasekaran, A., Dubey, R., & Fosso Wamba, S. (2017). Big data and analytics in operations and supply chain management: managerial aspects and practical challenges. *Production Planning and Control*, *28*(11–12), 873–876. https://doi.org/10.1080/09537287.2017.1336795
Park, H., Bellamy, M. A., & Basole, R. C. (2016). Visual analytics for supply network management: System design and evaluation. *Decision Support Systems*, *91*, 89–102. https://doi.org/10.1016/j.dss.2016.08.003
Parmar, D., Wu, T., Callarman, T., Fowler, J., & Wolfe, P. (2010). A clustering algorithm for supplier base management. *International Journal of Production Research*, *48*(13), 3803–3821. https://doi.org/10.1080/00207540902942891
Peng, D. X., & Lu, G. (2017). Exploring the Impact of Delivery Performance on Customer Transaction

Volume and Unit Price: Evidence from an Assembly Manufacturing Supply Chain. *Production and Operations Management*, *26*(5), 880–902. https://doi.org/10.1111/poms.12682

Petroni, A., & Braglia, M. (2000). Vendor selection using principal component analysis. *Journal of Supply Chain Management*, *36*(1), 63–69. https://doi.org/10.1111/j.1745-493X.2000.tb00078.x

Piramuthu, S. (2005). Machine learning for dynamic multi-product supply chain formation. *Expert Systems with Applications*, *29*(4), 985–990. https://doi.org/10.1016/j.eswa.2005.07.004

Prajogo, D., Chowdhury, M., Yeung, A. C. L., & Cheng, T. C. E. (2012). The relationship between supplier management and firms operational performance: A multi-dimensional perspective. *International Journal of Production Economics*, *136*(1), 123–130. https://doi.org/10.1016/j.ijpe.2011.09.022

Priore, P., Ponte, B., Rosillo, R., & de la Fuente, D. (2019). Applying machine learning to the dynamic selection of replenishment policies in fast-changing supply chain environments. *International Journal of Production Research*, *57*(11), 3663–3677. https://doi.org/10.1080/00207543.2018.1552369

Quang, H. T., Sampaio, P., Carvalho, M. S., Fernandes, A. C., Binh An, D. T., & Vilhenac, E. (2016). An extensive structural model of supply chain quality management and firm performance. *International Journal of Quality and Reliability Management*, *33*(4), 444–464. https://doi.org/10.1108/IJQRM-11-2014-0188

Roßmann, B., Canzaniello, A., von der Gracht, H., & Hartmann, E. (2018). The future and social impact of Big Data Analytics in Supply Chain Management: Results from a Delphi study. *Technological Forecasting and Social Change*, *130*(September 2017), 135–149. https://doi.org/10.1016/j.techfore.2017.10.005

Sahay, B. S., & Ranjan, J. (2008). Real time business intelligence in supply chain analytics. *Information Management and Computer Security*, *16*(1), 28–48. https://doi.org/10.1108/09685220810862733

Sanders, N. R. (2016). How to use big data to drive your supply chain. *California Management Review*, *58*(3), 26–48. https://doi.org/10.1525/cmr.2016.58.3.26

Sangari, M. S., & Razmi, J. (2015). Business intelligence competence, agile capabilities, and agile performance in supply chain An empirical study. *International Journal of Logistics Management*, *26*(2), 356–380. https://doi.org/10.1108/IJLM-01-2013-0012

Saunders, M., Lewis, P., & Thornhill, A. (2009). Research methods for business students. In *Pearson education*. https://doi.org/10.1080/09523367.2012.743996

Schein, E. (1999). *Process Consultation Revisited: Building the Helping Relationship*. Addison Wesley Longman.

Schneiderman, A. M. (1996). Metrics for the order fulfillment process (part 2). *Journal of Cost Management Management*, *10*(3).

Schoenherr, T., & Speier-Pero, C. (2015). Data science, predictive analytics, and big data in supply chain management: Current state and future potential. *Journal of Business Logistics*, *36*(1), 120–132. https://doi.org/10.1111/jbl.12082

Sener, A., Barut, M., Dag, A., & Yildirim, M. B. (2019). Impact of commitment, information sharing, and information usage on supplier performance: a Bayesian belief network approach. In *Annals of Operations Research* (Issue 0123456789). Springer US. https://doi.org/10.1007/s10479-019-03504-8

Singh, A., Shukla, N., & Mishra, N. (2018). Social media data analytics to improve supply chain management in food industries. *Transportation Research Part E: Logistics and Transportation Review*, *114*, 398–415. https://doi.org/10.1016/j.tre.2017.05.008

Singh, N. P., & Singh, S. (2019). Building supply chain risk resilience: Role of big data analytics in supply chain disruption mitigation. *Benchmarking*, *26*(7), 2318–2342. https://doi.org/10.1108/BIJ-10-2018-0346

Song, Z., & Kusiak, A. (2009). Optimising product configurations with a data-mining approach. *International Journal of Production Research*, *47*(7), 1733–1751. https://doi.org/10.1080/00207540701644235

Souza, G. C. (2014). Supply chain analytics. *Business Horizons*, *57*(5), 595–605. https://doi.org/10.1016/j.bushor.2014.06.004

Srinivasan, Ravi, & Swink, M. (2018). An Investigation of Visibility and Flexibility as Complements to Supply Chain Analytics: An Organizational Information Processing Theory Perspective. *Production and Operations Management*, *27*(10), 1849–1867. https://doi.org/10.1111/poms.12746

Srinivasan, Rengarajan, Giannikas, V., Kumar, M., Guyot, R., & McFarlane, D. (2019). Modelling food sourcing decisions under climate change: A data-driven approach. *Computers and Industrial Engineering*, *128*(July 2018), 911–919. https://doi.org/10.1016/j.cie.2018.10.048

Tang, C. S. (2006). Perspectives in supply chain risk management. *International Journal of Production Economics*, *103*(2), 451–488. https://doi.org/10.1016/j.ijpe.2005.12.006

Tiwari, S., Wee, H. M., & Daryanto, Y. (2018). Big data analytics in supply chain management between 2010 and 2016: Insights to industries. *Computers and Industrial Engineering*, *115*(October 2017), 319–330. https://doi.org/10.1016/j.cie.2017.11.017

Trkman, P., McCormack, K., De Oliveira, M. P. V., & Ladeira, M. B. (2010). The impact of business analytics on supply chain performance. *Decision Support Systems*, *49*(3), 318–327. https://doi.org/10.1016/j.dss.2010.03.007

Tsai, F. M., & Huang, L. J. W. (2017). Using artificial neural networks to predict container flows between the major ports of Asia. *International Journal of Production Research*, *55*(17), 5001–5010. https://doi.org/10.1080/00207543.2015.1112046

van der Spoel, S., Amrit, C., & van Hillegersberg, J. (2017). Predictive analytics for truck arrival time estimation: a field study at a European distribution centre. *International Journal of Production Research*, *55*(17), 5062–5078. https://doi.org/10.1080/00207543.2015.1064183

van Weele, A. J., & van Raaij, E. M. (2014). The future of purchasing and supply management research: About relevance and rigor. *Journal of Supply Chain Management*, *50*(1), 56–72. https://doi.org/10.1111/jscm.12042

Waller, M. A., & Fawcett, S. E. (2013). Data science, predictive analytics, and big data: A revolution that will transform supply chain design and management. *Journal of Business Logistics*, *34*(2), 77–84. https://doi.org/10.1111/jbl.12010

Wamba, S. F., Dubey, R., Gunasekaran, A., & Akter, S. (2020). The performance effects of big data analytics and supply chain ambidexterity: The moderating effect of environmental dynamism. *International Journal of Production Economics*, *222*(September 2019), 107498. https://doi.org/10.1016/j.ijpe.2019.09.019

Wang, G., Gunasekaran, A., Ngai, E. W. T., & Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. *International Journal of Production Economics*, *176*, 98–110. https://doi.org/10.1016/j.ijpe.2016.03.014

Wieland, A., Handfield, R. B., & Durach, C. F. (2016). Mapping the Landscape of Future Research Themes in Supply Chain Management. *Journal of Business Logistics*, *37*(3), 205–212. https://doi.org/10.1111/jbl.12131

Williams, B. D., Roh, J., Tokar, T., & Swink, M. (2013). Leveraging supply chain visibility for responsiveness: The moderating role of internal integration. *Journal of Operations Management*, *31*(7–8), 543–554. https://doi.org/10.1016/j.jom.2013.09.003

Wu, D. (2009). Supplier selection: A hybrid model using DEA, decision tree and neural network. *Expert Systems with Applications*, *36*(5), 9105–9112. https://doi.org/10.1016/j.eswa.2008.12.039

Wu, P. J., & Chaipiyaphan, P. (2019). Diagnosis of delivery vulnerability in a logistics system for logistics risk management. *International Journal of Logistics Management*, *31*(1), 43–58.

https://doi.org/10.1108/IJLM-02-2019-0069
Yesudas, M., Menon, G., & Ramamurthy, V. (2014). Intelligent operational dashboards for smarter commerce using big data. *IBM Journal of Research and Development*, *58*(5–6), 1–10. https://doi.org/10.1147/JRD.2014.2346131
Yu, C. C., & Wang, C. S. (2008). A hybrid mining approach for optimizing returns policies in e-retailing. *Expert Systems with Applications*, *35*(4), 1575–1582. https://doi.org/10.1016/j.eswa.2007.08.099
Yu, W., Chavez, R., Jacobs, M. A., & Feng, M. (2018). Data-driven supply chain capabilities and performance: A resource-based view. *Transportation Research Part E: Logistics and Transportation Review*, *114*, 371–385. https://doi.org/10.1016/j.tre.2017.04.002
Zhang, R., Li, J., Wu, S., & Meng, D. (2016). Learning to select supplier portfolios for service supply chain. *PLoS ONE*, *11*(5), 1–19. https://doi.org/10.1371/journal.pone.0155672
Zhao, K., & Yu, X. (2011). A case based reasoning approach on supplier selection in petroleum enterprises. *Expert Systems with Applications*, *38*(6), 6839–6847. https://doi.org/10.1016/j.eswa.2010.12.055
Zhou, G. (2016). Research on supplier performance evaluation system based on data mining with triangular fuzzy information. *Journal of Intelligent and Fuzzy Systems*, *31*(3), 2035–2042. https://doi.org/10.3233/JIFS-16396
Zhu, S., Song, J., Hazen, B. T., Lee, K., & Cegielski, C. (2018). How supply chain analytics enables operational supply chain transparency: An organizational information processing theory perspective. *International Journal of Physical Distribution and Logistics Management*, *48*(1), 47–68. https://doi.org/10.1108/IJPDLM-11-2017-0341
Zou, Z., Tseng, T. L., Sohn, H., Song, G., & Gutierrez, R. (2011). A rough set based approach to distributor selection in supply chain management. *Expert Systems with Applications*, *38*(1), 106–115. https://doi.org/10.1016/j.eswa.2010.06.021

APPENDIX 1 – DATA REQUIREMENTS AND COLLECTION

Orders dataset

Table 13 - Orders dataset: list of attributes and fields identified

Name	Description	Field name	Table name
Purchasing Document	Purchasing document number	EBELN	EKET, EKKO, EKPO
Item	Item number of purchasing document	EBELP	EKET, EKPO
Scheduled quantity	Quantity ordered	MENGE	EKET
Delivered quantity	Quantity delivered	WEMNG	EKET
Scheduled delivery date	Order delivery date	EINDT	EKET
Purchasing document type	Purchasing document type code	BSART	EKKO
Purchasing Organisation	Purchasing organisation code	EKORG	EKKO
Deletion indicator	Deletion indicator in Purchasing Document	LOEKZ	EKKO
Plant	Bosch plant code	WERKS	EKPO, MARC
ASN indicator	Indicator of ASN implementation	BSTAE	EKPO
Material	Material number	MATNR	EKPO, MARC
MRP type	MRP type code	DISMM	MARC

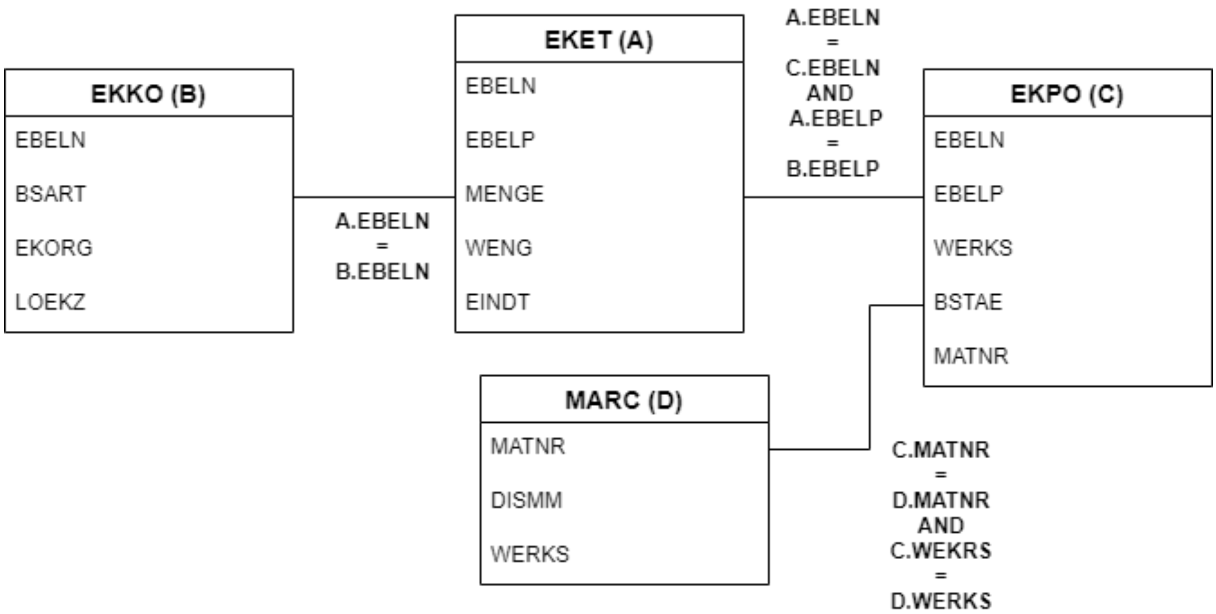


Figure 50 - Query diagram of Orders dataset tables

```
SELECT A.EBELN AS PurchDoc, A.EBELP as Item, C.MATNR, A.MENGE as SchedQTT, A.WEMNG as DelQtt, A.EINDT as DelDate
FROM [illegible].EKET_P45 A
LEFT JOIN (SELECT EBELN, BSART, EKORG, LOEKZ
          FROM [illegible].EKKO_P45) B
          ON A.EBELN = B.EBELN
LEFT JOIN (SELECT EBELN, EBELP, WERKS, BSTAE, MATNR
          FROM [illegible].EKPO_P45) C
          ON (A.EBELN = C.EBELN AND A.EBELP = C.EBELP)
LEFT JOIN (SELECT MATNR, DISMM, WERKS
          FROM [illegible].MARC_P45) D
          ON (C.MATNR = D.MATNR AND C.WERKS = D.WERKS)
WHERE A.EINDT >= 20200101
  AND B.BSART = 'LPA'
  AND (B.EKORG = '4991' OR B.EKORG = 'LOGA')
  AND B.LOEKZ = ' '
  AND C.WERKS = '8150'
  AND C.BSTAE = '0004'
  AND D.DISMM <> 'YI'
```

Figure 51 - SQL query to extract the Orders dataset

Material Master Dataset

Table 14 - Material Master dataset: list of attributes and fields identified

Name	Description	Field name	Table name
Material	Material number	MATNR	MARC, MBEW, MAKT
MRP	MRP controller code	DISPO	MARC
PTF	Planning Time Fence	FXHOR	MARC
ABC indicator	ABC indicator of material	MAABC	MARC
Plant	Bosch plant code	WERKS	MARC
MRP type	MRP type code	DISMM	MARC
Standard price	Price of material/price unit	STPRS	MBEW
Price Unit	Price unit of the standard price	STPRS	MBEW
Plant code for valuation area	Valuation area	BWKEY	MBEW
Material description	Description of the material	MAKTX	MAKT
Language	Language of the material description	SPRAS	MAKT

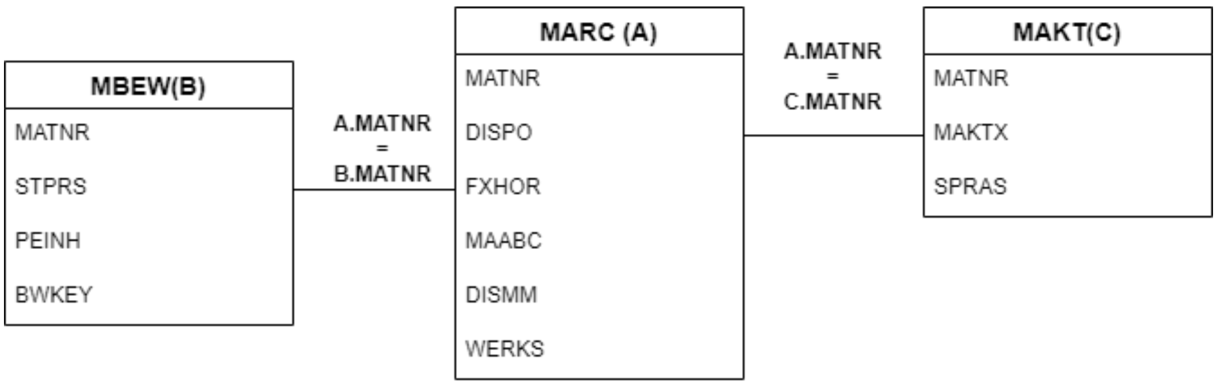


Figure 52 - Query diagram of Material Master dataset tables

```sql
SELECT A.MATNR as Material, A.DISPO as MRPCont, A.FXHOR as PTF, A.MAABC as ABC, B.STPRS as StandPrice,
B.PEINH as PriceUnit, C.MAKTX as MatDescrip, A.DISMM as MRPType
FROM [redacted].MARC_P45 A
LEFT JOIN (SELECT MATNR, STPRS, PEINH, BWKEY
          FROM [redacted].MBEW_P45) B
          ON A.MATNR = B.MATNR
LEFT JOIN (SELECT MATNR, MAKTX, SPRAS
          FROM [redacted].MAKT_P45) C
          ON A.MATNR = C.MATNR
WHERE C.SPRAS = 'E'
  AND A.WERKS = '8150'
  AND B.BWKEY = '8150'
  AND A.DISPO IN ('102','103','104','105','106','107','108','109','110','114','115','116','117',
'118','120','121','123','128','129','131','141','150','151','152','155','156','157','158','159',
'160','161','162','166','167','168','170','172','173','175','177','178','201','202','203','208',
'209','211','212','222','240','241','242','250','254','256','257','260','266','267','269','270',
'271','273','274','275','276','277','278','279','280','282','283','286','291')
```

Figure 53 - SQL query to extract the Material Master dataset

Deliveries (ASNs) dataset

Table 15 - Deliveries (ASNs) dataset: list of attributes and fields identified

Name	Description	Field name	Table name
Delivery number	Delivery identifier	VBELN	LIPS, LIKP, VBUK
Item	Item number of purchasing document	VGPOS	LIPS
Purchasing Document	Purchasing document number	VGBEL	LIPS
Material	Material number	MATNR	LIPS
Delivery quantity	Quantity being delivered	LFIMG	LIPS
Plant	Bosch plant code	WERKS	LIPS
Delivery note number	External identification of delivery note	LIFEX	LIKP
Vendor	Supplier identification code	LIFNR	LIKP
Delivery date	Estimated time of arrival (ETA)	LFDAT	LIKP
Delivery type	Specifies the type of delivery	LFART	LIKP
Document date	Date of creation of ASN	BLDAT	LIKP
ETD	Estimated time of departure	TDDAT	LIKP
Total goods movement status	Status of ASN	WBSTK	VBUK
Purchasing Document	Purchasing document number	EBELN	EKKO
Purchasing document type	Purchasing document type code	BSART	EKKO
Purchasing organisation	Purchasing organisation code	EKORG	EKKO
Deletion indicator	Deletion indicator in Purchasing Document	LOEKZ	EKKO

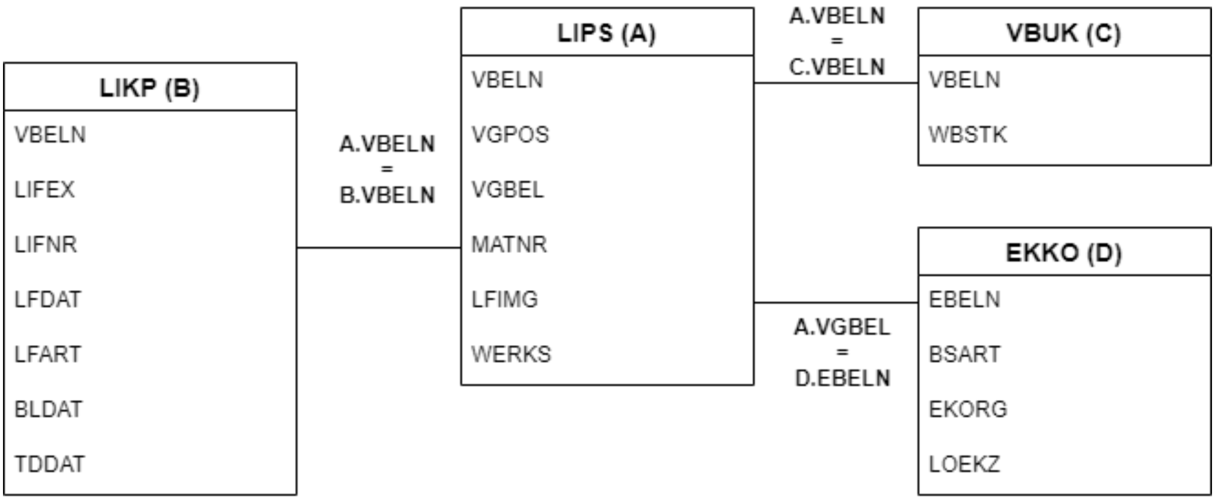


Figure 54 - Query diagram of Deliveries (ASNs) dataset tables

```
SELECT A.VBELN as DevliveryNr, A.VGPOS as RefItem, A.VGBEL as PurchDoc, A.MATNR as Material,
A.LFIMG as DelQtt, B.LIFEX as DN, B.LIFNR as Vendor, B.LFDAT as DeliveryDate, B.BLDAT as DocumentDate,
B.TDDAT as ETD, B.LFART as DeliveryType, C.WBSTK as TotalGoodsMovStat
FROM [illegible].LIPS_P45 A
LEFT JOIN (SELECT VBELN, LIFEX, LIFNR, LFDAT, LFART, BLDAT, TDDAT
          FROM [illegible].LIKP_P45) B
          ON A.VBELN = B.VBELN
LEFT JOIN (SELECT VBELN, WBSTK
          FROM [illegible].VBUK_P45) C
          ON A.VBELN = C.VBELN
LEFT JOIN (SELECT EBELN, BSART, EKORG, LOEKZ
          FROM [illegible].EKKO_P45) D
          ON A.VGBEL = D.EBELN
WHERE A.WERKS = '8150'
AND B.LFART = 'EL'
AND B.LFDAT >= 20200101
AND D.BSART = 'LPA'
AND (D.EKORG = '4991' OR D.EKORG = 'LOGA')
```

Figure 55 - SQL query to extract the Deliveries (ASNs) dataset

Order Releases dataset

Table 16 - Order Releases dataset: list of attributes and fields identified

Name	Description	Field name	Table name
Purchasing Document	Purchasing document number	EBELN	EKEK, EKEH, EKPO, EKKO
Item	Item number of purchasing document	EBELP	EKEK, EKEH, EKPO
Release number	Number of order release	ABRUF	EKEK, EKEH
Release date	Date when the release was sent to the supplier	ABRDT	EKEK
Cumulative received quantity	Cumulative received quantity by the release date	ABEFZ	EKEK
End of production release	End date of production release	ABFDE	EKEK
End of material release	End date of material release	ABMDE	EKEK
MRP	MRP controller code	DISPO	EKEK
Scheduled delivery date	Order delivery date	EINDT	EKEH
Scheduled quantity	Quantity ordered	MENGE	EKEH
Delivered quantity	Quantity delivered	WEMNG	EKEH
Material	Material number	MATNR	EKPO, MARC
Plant	Bosch plant code	WERKS	EKPO, MARC
Deletion indicator	Deletion indicator in Purchasing Document	LOEKZ	EKPO
ASN indicator	Indicator of ASN implementation	BSTAE	EKPO
Purchasing document type	Purchasing document type code	BSART	EKKO
Purchasing organisation	Purchasing organisation code	EKORG	EKKO
MRP type	MRP type code	DISMM	MARC
Cumulative scheduled quantity	Cumulative scheduled quantity by the release date	(Calculated column)	(Calculated column)

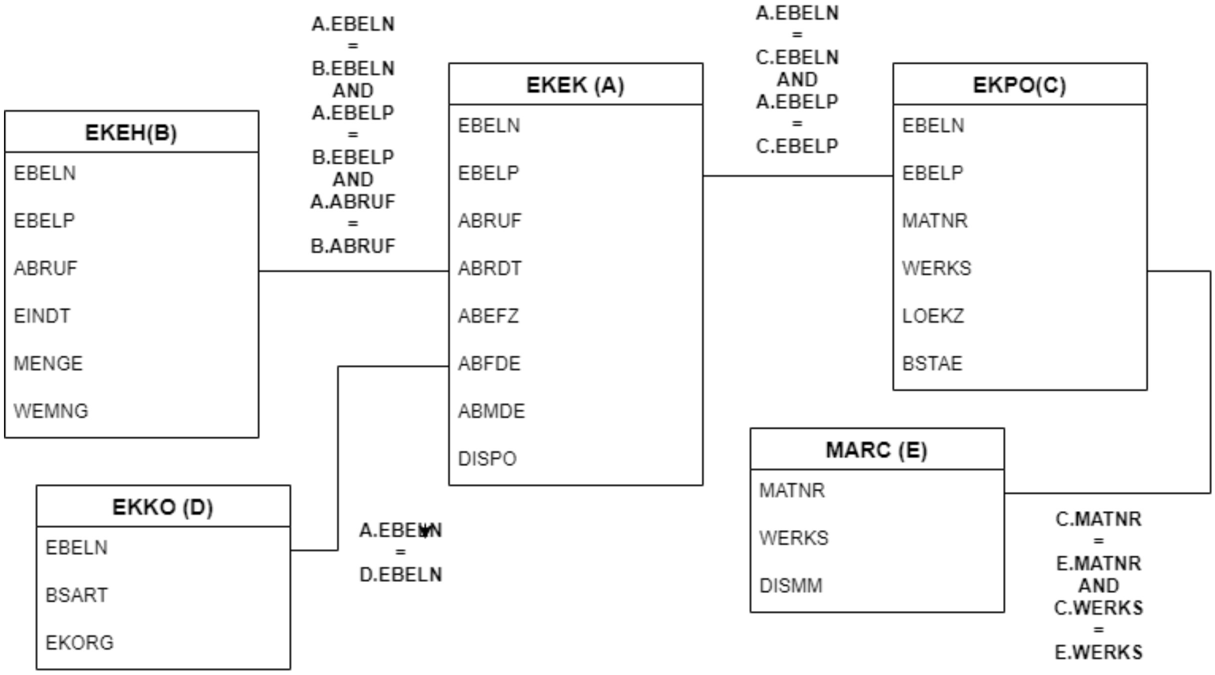


Figure 56 - Query diagram of Order Releases dataset tables

```
SELECT A.EBELN as PurchDoc, A.EBELP as Item, A.ABRUF as ReleaseNo, A.ABRDT as ReleaseDate, A.ABEFZ as CumRecQtt,
A.ABFDE as EndProdRelease, A.ABMDE as EndMatRelease, A.DISPO as MRP, B.EINDT as DeliveryDate, B.MENGE as ScheduledQtt,
B.WEMNG as DeliveredQtt, A.ABEFZ +
(SUM(B.MENGE - B.WEMNG) OVER (PARTITION BY A.EBELN, A.EBELP, A.ABRUF ORDER BY A.ABRUF, B.EINDT)) as CumulativeScheduled
FROM [redacted].EKEK_P45 A
RIGHT JOIN (SELECT EBELN, EBELP, ABRUF, EINDT, MENGE, WEMNG
          FROM [redacted].EKEH_P45) B
          ON (A.EBELN = B.EBELN AND A.EBELP = B.EBELP AND A.ABRUF=B.ABRUF)
LEFT JOIN (SELECT EBELN, EBELP, MATNR, WERKS, LOEKZ, BSTAE
          FROM [redacted].EKPO_P45) C
          ON (A.EBELN = C.EBELN AND A.EBELP = C.EBELP)
LEFT JOIN (SELECT EBELN, BSART, EKORG
          FROM [redacted].EKKO_P45) D
          ON A.EBELN = D.EBELN
LEFT JOIN (SELECT MATNR, DISMM, WERKS
          FROM [redacted].MARC_P45) E
          ON (C.MATNR = E.MATNR AND C.WERKS = E.WERKS)
WHERE A.ABRDT >= TO_CHAR (sysdate -200, 'YYYYMMDD')
  AND B.EINDT <= TO_CHAR (sysdate + 300, 'YYYYMMDD')
  AND A.DISPO IN ('102','103','104','105','106','107','108','109','110','114','115','116','117','118','120','121',
  '123','128','129','131','141','150','151','152','155','156','157','158','159','160','161','162','166','168','170',
  '172','173','175','177','178','201','202','203','208','209','211','212','222','240','241','242','250','254','256',
  '257','260','266','267','269','270','271','273','274','275','276','277','278','279','280','282','283','286','291')
  AND C.WERKS = '8150'
  AND C.LOEKZ = ' '
  AND D.BSART = 'LPA'
  AND E.DISMM <> 'YI'
```

Figure 57 - SQL query to extract the Order Releases dataset

Material Receipts dataset

Table 17 - Material Receipts dataset: list of attributes and fields identified

Name	Description	Field name	Table name
Purchasing Document	Purchasing document number	EBELN	MSEG
Item	Item number of purchasing document	EBELP	MSEG
Movement type	Type of movement (inventory management)	BWART	MSEG
Material	Material number	MATNR	MSEG
Quantity	Material movement quantity	MENGE	MSEG
Date	Date of movement	BUDAT_MKPF	MSEG
Plant	Bosch plant code	WERKS	MSEG

```
SELECT A.EBELN as PurchDoc, A.EBELP as Item, A.BWART as MovementType, A.MATNR as Material,
A.MENGE as Quantity, A.BUDAT_MKPF as EntryDate
FROM [redacted].MSEG_P45 A
WHERE A.WERKS = '8150'
  AND A.BWART IN (101, 102 , 122)
  AND A.BUDAT_MKPF > TO_CHAR (sysdate -250, 'YYYYMMDD')
```

Figure 58 - SQL query to extract the Material Receipts dataset

APPENDIX 2 – DAX FORMULAS

```
Date table formula: creates a date table, used to create connections between dates and date formates

Date =
ADDCOLUMNS (
CALENDAR (DATE(2019,1,1), DATE(2025,12,31)),
"DateAsInteger", FORMAT ( [Date], "YYYYMMDD" ),
"Year", YEAR ( [Date] ),
"Monthnumber", FORMAT ( [Date], "MM" ),
"YearMonthnumber", FORMAT ( [Date], "YYYY/MM" ),
"YearMonthShort", FORMAT ( [Date], "YYYY/mmm" ),
"MonthNameShort", FORMAT ( [Date], "mmm" ),
"MonthNameLong", FORMAT ( [Date], "mmmm" ),
"DayOfWeekNumber", WEEKDAY ( [Date] ),
"DayOfWeek", FORMAT ( [Date], "dddd" ),
"DayOfWeekShort", FORMAT ( [Date], "ddd" ),
"Quarter", "Q" & FORMAT ( [Date], "Q" ),
"YearQuarter", FORMAT ( [Date], "YYYY" ) & "/Q" & FORMAT ( [Date], "Q" )
)
```

Figure 59 - Formula to create dates table

```
ETD/ASN Creation Date =
IF (
    Deliveries[ETD] = "00000000",
    DATE ( LEFT ( Deliveries[DOCUMENTDATE], 4 ), MID ( Deliveries[DOCUMENTDATE], 5, 2 ), RIGHT ( Deliveries[DOCUMENTDATE], 2 ) ),
    DATE ( LEFT ( Deliveries[ETD], 4 ), MID ( Deliveries[ETD], 5, 2 ), RIGHT ( Deliveries[ETD], 2 ) )
)
```

Figure 60 - ETD formula

```
PurchDocItem = Deliveries[PURCHDOC] & "-" & Deliveries[ITEM]
```

Figure 61 - Formula to create the primary key

```
Status = IF(Deliveries[TOTALGOODSMOVSTAT] <> "C", "Open", "Closed")
```

Figure 62 - Delivery status formula

```
Quantity_Entry = IF('Material Entries'[MOVEMENTTYPE] = "101", 'Material Entries'[QUANTITY], -'Material Entries'[QUANTITY])
```

Figure 63 - Support formula to other calculations

```
OpenQtt = 'Open Orders'[SCHEDQTT]-'Open Orders'[DELQTT]
```

Figure 64 - Formula to calculate open order quantity

```
PurchDocItem = 'Open Orders'[PURCHDOC] & "-" & 'Open Orders'[ITEM]
```

Figure 65 - Formula to create the primary key

```
Status = IF('Open Orders'[OpenQtt] > 0, "Open", "Closed")
```

Figure 66 - Order status formula

```
Liability in Material Release = MAX('Order Releases'[Quantity in Material Release] - 'Order Releases'[Quantity Received since Release Date])
```

Figure 67 - Formula to calculate material liability

```
Quantity in Material Release =
VAR PurchDocItem = 'Order Releases'[PurchDocItem]
VAR ReleaseDate = 'Order Releases'[RELEASEDATE]
RETURN
    CALCULATE (
        SUM ( 'Order Releases'[Open Qtt] ),
        FILTER ( 'Order Releases', 'Order Releases'[PurchDocItem] = PurchDocItem ),
        FILTER ( 'Order Releases', 'Order Releases'[RELEASEDATE] = ReleaseDate ),
        FILTER (
            'Order Releases',
            'Order Releases'[DELIVERYDATE]
                <= (
                    'Order Releases'[RELEASEDATE]
                        + LOOKUPVALUE (
                            Purch_Doc_Inf[TRADEOFFZONE],
                            Purch_Doc_Inf[PurchDocItem], 'Order Releases'[PurchDocItem]
                        )
                )
        )

    )
```

Figure 68 - Support formula to material liability calculation

```
Liability Production Release = MAX('Order Releases'[Quantity in Production Release] - 'Order Releases'[Quantity Received since Release Date])
```

Figure 69 - Formula to calculate production liability

```
Quantity in Production Release =
VAR PurchDocItem = 'Order Releases'[PurchDocItem]
VAR ReleaseDate = 'Order Releases'[RELEASEDATE]
RETURN
    CALCULATE (
        SUM ( 'Order Releases'[Open Qtt] ),
        FILTER ( 'Order Releases', 'Order Releases'[PurchDocItem] = PurchDocItem ),
        FILTER ( 'Order Releases', 'Order Releases'[RELEASEDATE] = ReleaseDate ),
        FILTER (
            'Order Releases',
            'Order Releases'[DELIVERYDATE]
                <= (
                    'Order Releases'[RELEASEDATE]
                        + LOOKUPVALUE (
                            Purch_Doc_Inf[FIRMZONE],
                            Purch_Doc_Inf[PurchDocItem], 'Order Releases'[PurchDocItem]
                        )
                )
        )
    )
```

Figure 70 - Support formula to material liability calculation

```
Liability PTF =
IF (
    ISBLANK ( 'Order Releases'[Quantity in PTF] - 'Order Releases'[Quantity Received since Release Date] ),
    0,
    'Order Releases'[Quantity in PTF] - 'Order Releases'[Quantity Received since Release Date]
)
```

Figure 71 - Formula to support the calculation of quantities Bosch should receive considering order changes in PTF

```
Quantity Received since Release Date =
VAR PurchDocItem = 'Order Releases'[PurchDocItem]
RETURN
    IF (
        ISBLANK (
            CALCULATE (
                SUM ( 'Material Entries'[Quantity_Entry] ),
                FILTER ( 'Material Entries', 'Material Entries'[PurchDoc Item] = PurchDocItem ),
                FILTER (
                    'Material Entries',
                    'Material Entries'[ENTRYDATE] >= 'Order Releases'[RELEASEDATE]
                )
            )
        ),
        0,
        CALCULATE (
            SUM ( 'Material Entries'[Quantity_Entry] ),
            FILTER ( 'Material Entries', 'Material Entries'[PurchDoc Item] = PurchDocItem ),
            FILTER (
                'Material Entries',
                'Material Entries'[ENTRYDATE] >= 'Order Releases'[RELEASEDATE]
            )
        )
    )
```

Figure 72 - Formula to support all liability and order changes calculations

```
Quantity to be received considering changes in PTF =
IF (
    MAX ( Purch_Doc_Inf[Planned Quantity in PTF] )
        > CALCULATE (
            MAX ( 'Order Releases'[Liability PTF] ),
            FILTER (
                'Order Releases',
                'Order Releases'[RELEASEDATE]
                    >= TODAY ()
                        - LOOKUPVALUE (
                            Purch_Doc_Inf[PTF],
                            Purch_Doc_Inf[PurchDocItem], 'Order Releases'[PurchDocItem]
                        ) - 7
            )
        ),
    MAX ( Purch_Doc_Inf[Planned Quantity in PTF] ),
    CALCULATE (
        MAX ( 'Order Releases'[Liability PTF] ),
        FILTER (
            'Order Releases',
            'Order Releases'[RELEASEDATE]
                >= TODAY ()
                    - LOOKUPVALUE (
                        Purch_Doc_Inf[PTF],
                        Purch_Doc_Inf[PurchDocItem], 'Order Releases'[PurchDocItem]
                    ) - 7
        )
    )
)
```

Figure 73 - Formula to calculate the quantities Bosch should receive considering order changes inside the PTF

```
Orders_Deliveries =
UNION (
    SELECTCOLUMNS (
        'Open Orders',
        "Movement", 'Open Orders'[Movement],
        "Purch Doc Item", 'Open Orders'[PurchDocItem],
        "Purch Doc", 'Open Orders'[PURCHDOC],
        "Quantity", - 'Open Orders'[SCHEDQTT],
        "Date", 'Open Orders'[DelDate],
        "Status", 'Open Orders'[Status],
        "Open Quantity", - 'Open Orders'[OpenQtt],
        "Delivery No", "--",
        "External Delivery ID", "--",
        "ETD / ASN Creation Date", "--"
    ),
    SELECTCOLUMNS (
        Deliveries,
        "Movement", Deliveries[Movement],
        "Purch Doc Item", Deliveries[PurchDocItem],
        "Purch Doc", Deliveries[PURCHDOC],
        "Quantity", Deliveries[DELQTT],
        "Date", Deliveries[DELIVERYDATE],
        "Status", Deliveries[Status],
        "Open Quantity", Deliveries[DELQTT],
        "Delivery No", Deliveries[DEVLIVERYNR],
        "External Delivery ID", Deliveries[DN],
        "ETD / ASN Creation Date", FORMAT(Deliveries[ETD/ASN Creation Date], "dd/mm/yyyy")
    )
)
```

Figure 74 - Formula to create a table that overlaps deliveries and orders to evaluate deliveries status

```
Cumulative_Open =
VAR Purch_Doc = 'Orders_Deliveries'[Purch Doc Item]
RETURN
    CALCULATE (
        SUM ( 'Orders_Deliveries'[Open Quantity] ),
        ALL ( 'Orders_Deliveries' ),
        'Orders_Deliveries'[Purch Doc Item] = Purch_Doc,
        'Orders_Deliveries'[Date] <= EARLIER ( 'Orders_Deliveries'[Date].[Date] ),
        'Orders_Deliveries'[Status] = "Open"
    )
```

Figure 75 - Formula that calculates cumulative quantity difference between delivered and ordered quantities

```
Cumulative_Open_Value =
'Orders_Deliveries'[Cumulative_Open]
    * (
        LOOKUPVALUE (
            MM[STANDPRICE],
            MM[MATERIAL],
                LOOKUPVALUE (
                    Purch_Doc_Inf[Material],
                    Purch_Doc_Inf[PurchDocItem], 'Orders_Deliveries'[Purch Doc Item])
        )
            / LOOKUPVALUE (
                MM[PRICEUNIT],
                MM[MATERIAL],
                    LOOKUPVALUE (
                        Purch_Doc_Inf[Material],
                        Purch_Doc_Inf[PurchDocItem], 'Orders_Deliveries'[Purch Doc Item])
            )
    )
```

Figure 76 - Formula that calculates the value of the cumulative quantity difference between delivered and ordered quantities

```
Delivery Status Classifier =
VAR Purch_Doc = 'Orders_Deliveries'[Purch Doc Item]
RETURN
    IF (
        AND (
            'Orders_Deliveries'[Movement] = "ASN",
            AND (
                'Orders_Deliveries'[Status] = "Open",
                AND (
                    'Orders_Deliveries'[Open Quantity] > 0,
                    'Orders_Deliveries'[Cumulative_Open] > 0
                )
            )
        ),
        1,
        IF (
            AND (
                'Orders_Deliveries'[Status] = "Open",
                OR (
                    AND (
                        'Orders_Deliveries'[Movement] = "ASN",
                        CALCULATE (
                            SUM ( 'Orders_Deliveries'[Open Quantity] ),
                            ALL ( 'Orders_Deliveries' ),
                            'Orders_Deliveries'[Purch Doc Item] = Purch_Doc,
                            'Orders_Deliveries'[Date] < EARLIER ( 'Orders_Deliveries'[Date].[Date] ),
                            'Orders_Deliveries'[Status] = "Open"
                        ) < 0
                    ),
                    AND (
                        'Orders_Deliveries'[Movement] = "Order",
                        AND (
                            'Orders_Deliveries'[Cumulative_Open] < 0,
                            'Orders_Deliveries'[Date].[Date]
                                < LOOKUPVALUE (
                                    Purch_Doc_Inf[End of PTF],
                                    Purch_Doc_Inf[PurchDocItem], 'Orders_Deliveries'[Purch Doc Item]
                                )
                        )
                    )
                )
            ),
            2,
            IF (
                AND (
                    'Orders_Deliveries'[Status] = "Open",
                    AND (
                        'Orders_Deliveries'[Movement] = "ASN",
                        AND (
                            'Orders_Deliveries'[Open Quantity] > 0,
                            'Orders_Deliveries'[Cumulative_Open] = 0
                        )
                    )
                ),
                3,
                0
            )
        )
    )
```

Figure 77 - Formula that attributes a number code to deliveries (delivery classifier) according to their status (late, early, or on-time deliveries)

```
Delivery Status =
IF (
    'Orders_Deliveries'[Delivery Status Dummy] = 1,
    "Potential Early Delivery",
    IF (
        'Orders_Deliveries'[Delivery Status Dummy] = 2,
        "Potential Late Delivery",
        IF ( 'Orders_Deliveries'[Delivery Status Dummy] = 3, "On-time", "--" )
    )
)
```

Figure 78 - Formula that, according to the delivery classifier, shows the status of the delivery (late, early, or on-time deliveries)

```
Early/Late Quantity =
IF (
    Orders_Deliveries[Delivery Status Dummy] = 1,
    IF (
        Orders_Deliveries[Cumulative_Open] >= Orders_Deliveries[Open Quantity],
        Orders_Deliveries[Open Quantity],
        Orders_Deliveries[Cumulative_Open]
    ),
    IF (
        Orders_Deliveries[Delivery Status Dummy] = 2,
        IF (
            Orders_Deliveries[Movement] = "Order",
            - Orders_Deliveries[Open Quantity],
            Orders_Deliveries[Open Quantity]
        ),
        0
    )
)
```

Figure 79 - Formula that calculates the quantity that is being delivered early or late

```
Early/Late Quantity Value =
Orders_Deliveries[Early/Late Quantity]
    * (
        LOOKUPVALUE (
            MM[STANDPRICE],
            MM[MATERIAL],
                LOOKUPVALUE (
                    Purch_Doc_Inf[Material],
                    Purch_Doc_Inf[PurchDocItem], 'Orders_Deliveries'[Purch Doc Item]
                )
        )
            / LOOKUPVALUE (
                MM[PRICEUNIT],
                MM[MATERIAL],
                    LOOKUPVALUE (
                        Purch_Doc_Inf[Material],
                        Purch_Doc_Inf[PurchDocItem], 'Orders_Deliveries'[Purch Doc Item]
                    )
            )
    )
```

Figure 80 - Formula that calculates the value of the quantity that is being delivered early or late

```
Open Quantity Value =
'Orders_Deliveries'[Open Quantity]
    * (
        LOOKUPVALUE (
            MM[STANDPRICE],
            MM[MATERIAL],
                LOOKUPVALUE (
                    Purch_Doc_Inf[Material],
                    Purch_Doc_Inf[PurchDocItem], 'Orders_Deliveries'[Purch Doc Item]
                )
        )
            / LOOKUPVALUE (
                MM[PRICEUNIT],
                MM[MATERIAL],
                    LOOKUPVALUE (
                        Purch_Doc_Inf[Material],
                        Purch_Doc_Inf[PurchDocItem], 'Orders_Deliveries'[Purch Doc Item]
                    )
            )
    )
```

Figure 81 - Formula that calculates the total value of a delivery or an order

```
Coverage =
VAR PurchDocItem = Purch_Doc_Inf[PurchDocItem]
RETURN
    IF (
        ISBLANK (
            CALCULATE (
                FIRSTDATE ( 'Open Orders'[DELDATE] ),
                'Open Orders'[PurchDocItem] = PurchDocItem,
                FILTER ( 'Open Orders', 'Open Orders'[Coverage Quantity] <= 0 )
            )
        ),
        "Overstock",
        FORMAT (
            CALCULATE (
                FIRSTDATE ( 'Open Orders'[DELDATE] ),
                'Open Orders'[PurchDocItem] = PurchDocItem,
                FILTER ( 'Open Orders', 'Open Orders'[Coverage Quantity] <= 0 )
            ),
            "dd/mm/yyyy"
        )
    )
```

Figure 82 - Formula that calculates order coverage, i.e., the date until which the deliveries cover the open orders

```
Coverage Quantity =
VAR Purch_Doc_Item = 'Open Orders'[PurchDocItem]
RETURN
    LOOKUPVALUE (
        Purch_Doc_Inf[Total ASN Qtt],
        Purch_Doc_Inf[PurchDocItem], 'Open Orders'[PurchDocItem]
    )
        - CALCULATE (
            SUM ( 'Open Orders'[OpenQtt] ),
            FILTER ( 'Open Orders', 'Open Orders'[PurchDocItem] = Purch_Doc_Item ),
            'Open Orders'[DELDATE] <= EARLIER ( 'Open Orders'[DELDATE] )
        )
```

Figure 83 - Formula that supports the calculation of order coverage

```
Planned Quantity in PTF =
VAR DelDate = Purch_Doc_Inf[End of PTF].[Date]
VAR PurchDoc = Purch_Doc_Inf[PurchDocItem]
RETURN
    CALCULATE (
        SUM ( 'Open Orders'[OpenQtt] ),
        FILTER ( 'Open Orders', 'Open Orders'[DelDate] <= DelDate ),
        FILTER ( 'Open Orders', 'Open Orders'[PurchDocItem] = PurchDoc ))
```

Figure 84 - Formula that calculates the total open orders' quantity inside the current PTF

```
End of PTF = TODAY() + Purch_Doc_Inf[PTF]
```

Figure 85 - Formula that calculates the end date of the PTF

```
Total ASN Qtt =
VAR PurchDoc = Purch_Doc_Inf[PurchDocItem]
RETURN
    CALCULATE (
        SUM ( Deliveries[DELQTT] ),
        FILTER ( Deliveries, Deliveries[PurchDocItem] = PurchDoc ),
        FILTER ( Deliveries, Deliveries[TOTALGOODSMOVSTAT] <> "C" ))
```

Figure 86 - Formula that calculates the total quantity in transit according to ASNs

```
Delta Quantity = Purch_Doc_Inf[Total ASN Qtt] - Purch_Doc_Inf[Planned Quantity in PTF]
```

Figure 87 - Formula that calculates the absolute quantity deviation of deliveries from open orders

```
Delta % = Purch_Doc_Inf[Delta Quantity] / Purch_Doc_Inf[Planned Quantity in PTF]
```

Figure 88 – Formula that calculates the percentage of deviation of deliveries from open orders

```
Delta Value =
Purch_Doc_Inf[Delta Quantity]
    * (
        LOOKUPVALUE ( MM[STANDPRICE], MM[MATERIAL], Purch_Doc_Inf[Material] )
            / LOOKUPVALUE ( MM[PRICEUNIT], MM[MATERIAL], Purch_Doc_Inf[Material] )
    )
```

Figure 89 - Formula that calculates the value of the deviation quantity of the deliveries from the open orders

```
Incoterm =
IF (
    OR (
        OR ( Purch_Doc_Inf[INCOTERM1] = "EXW", Purch_Doc_Inf[INCOTERM1] = "FCA" ),
        Purch_Doc_Inf[INCOTERM1] = "FOB"
    ),
    "FCA",
    "DAP/DDP"
)
```

Figure 90 - Incoterm formula

```
Total Value in Transit =
Purch_Doc_Inf[Total ASN Qtt]
    * (
        LOOKUPVALUE ( MM[STANDPRICE], MM[MATERIAL], Purch_Doc_Inf[Material] )
            / LOOKUPVALUE ( MM[PRICEUNIT], MM[MATERIAL], Purch_Doc_Inf[Material] )
    )
```

Figure 91 - Formula that calculates the value of the total quantity in transit according to ASNs

APPENDIX 3 – DASHBOARD TABS

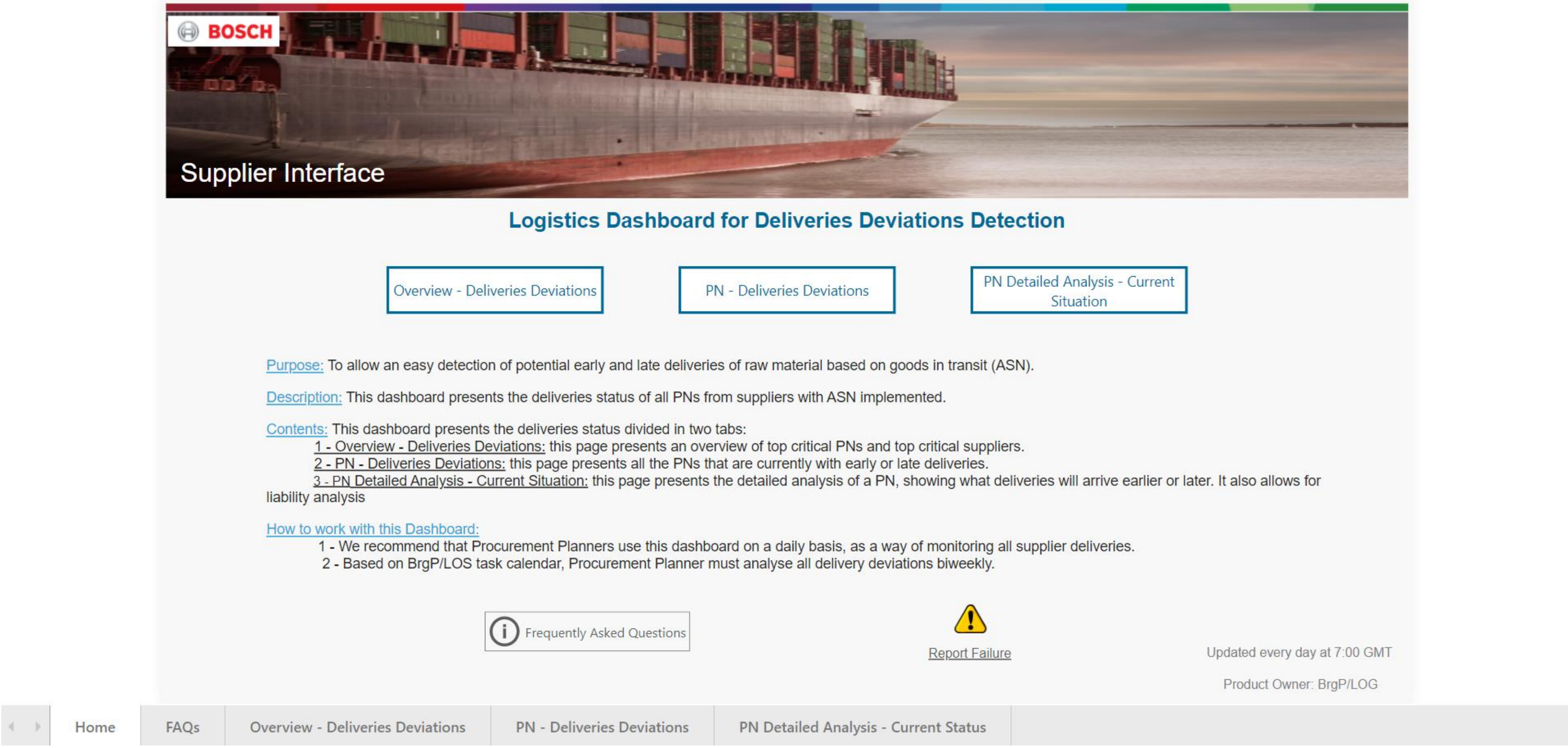


Figure 92 - Early deliveries dashboard: Home tab

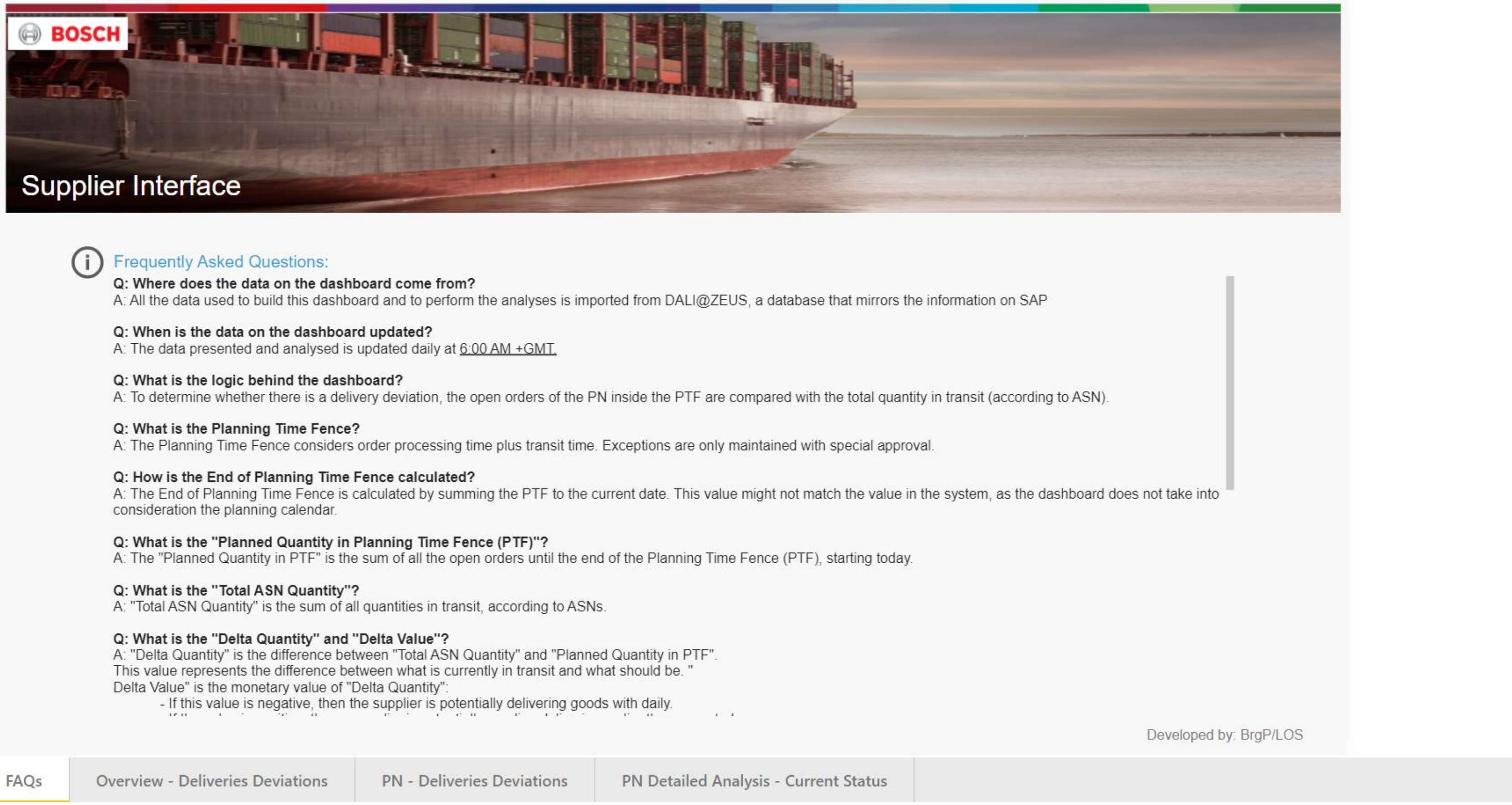


Figure 93 - Early deliveries dashboard: FAQs tab

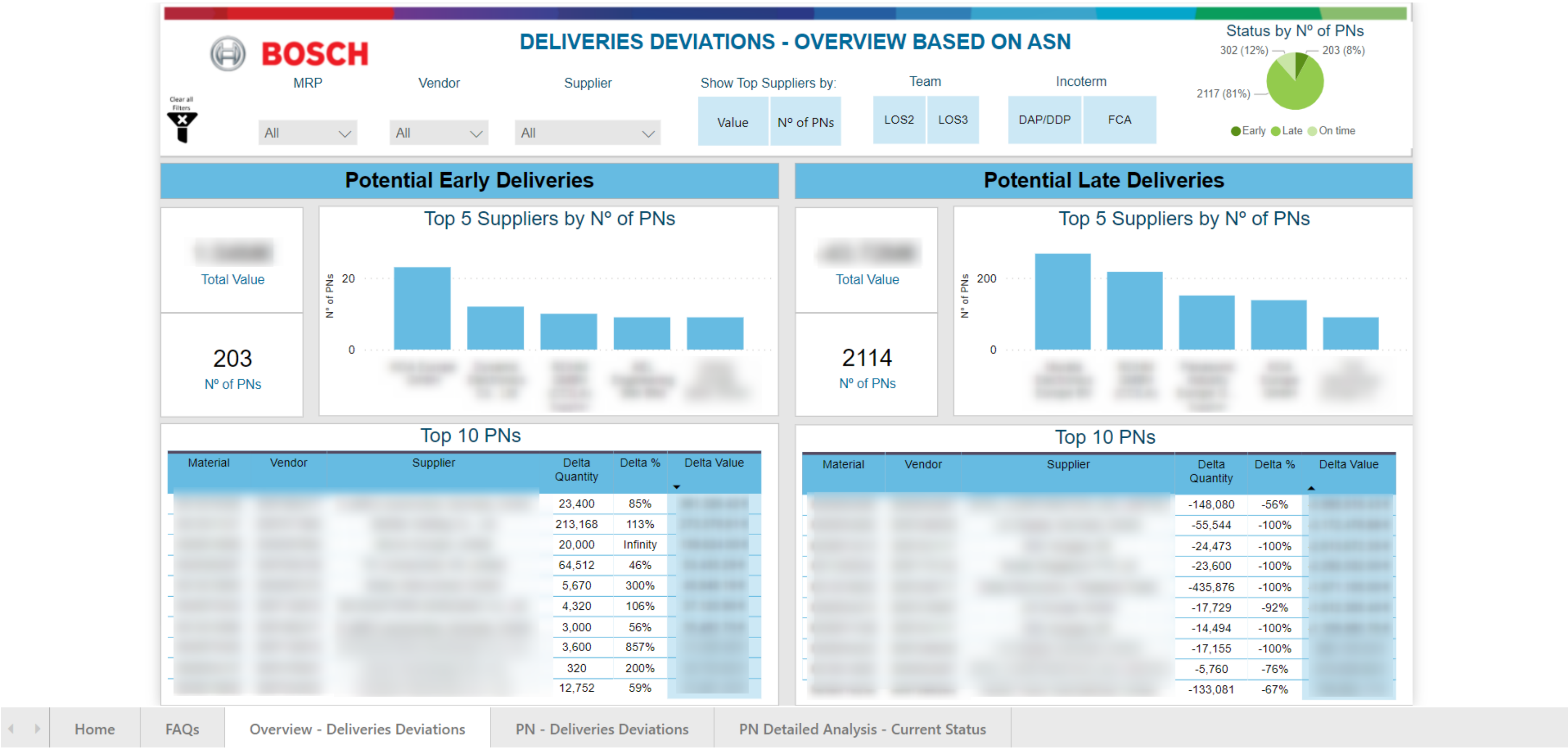
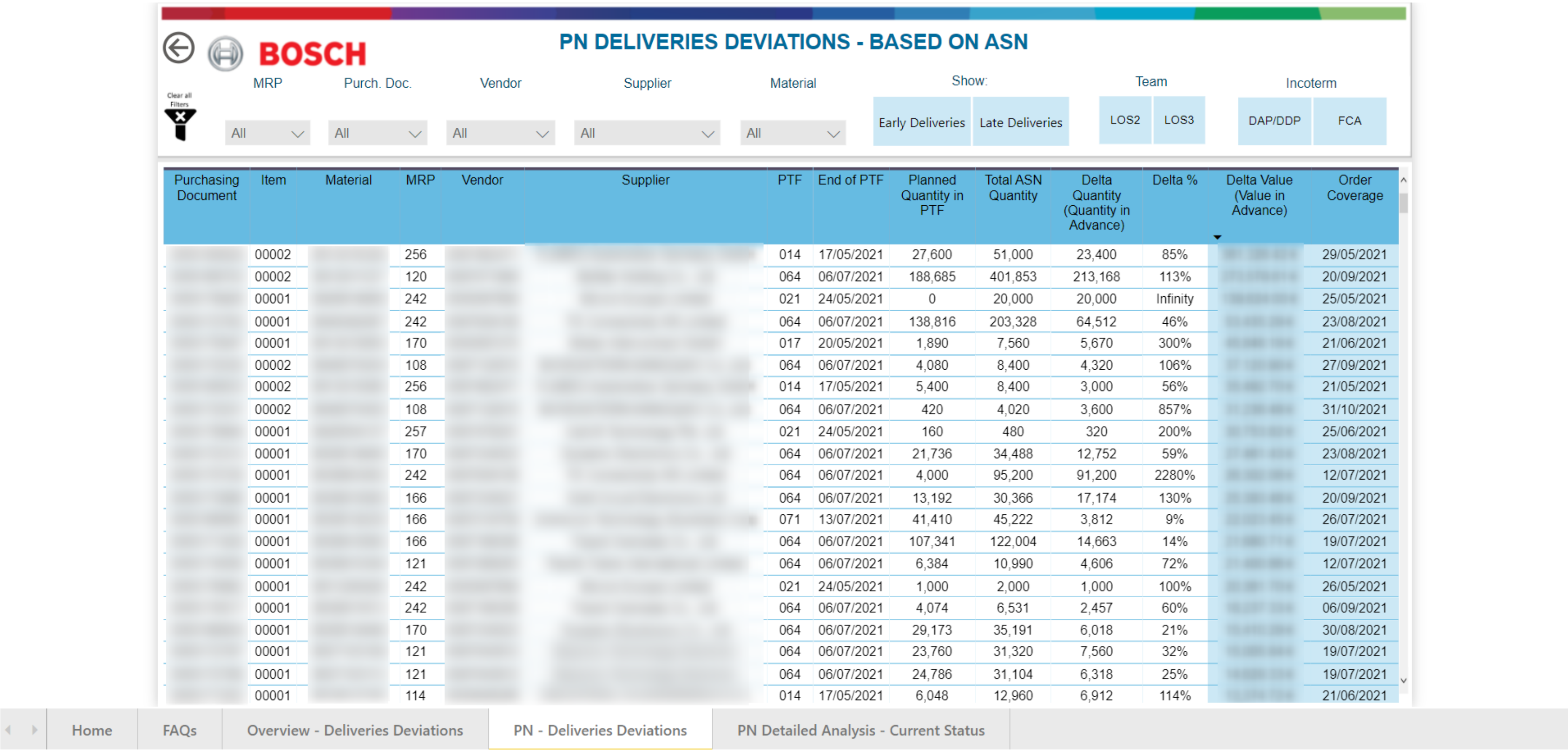


Figure 94 - Early deliveries dashboard: Current status overview tab



Purchasing Document	Item	Material	MRP	Vendor	Supplier	PTF	End of PTF	Planned Quantity in PTF	Total ASN Quantity	Delta Quantity (Quantity in Advance)	Delta %	Delta Value (Value in Advance)	Order Coverage
	00002		256			014	17/05/2021	27,600	51,000	23,400	85%		29/05/2021
	00002		120			064	06/07/2021	188,685	401,853	213,168	113%		20/09/2021
	00001		242			021	24/05/2021	0	20,000	20,000	Infinity		25/05/2021
	00001		242			064	06/07/2021	138,816	203,328	64,512	46%		23/08/2021
	00001		170			017	20/05/2021	1,890	7,560	5,670	300%		21/06/2021
	00002		108			064	06/07/2021	4,080	8,400	4,320	106%		27/09/2021
	00002		256			014	17/05/2021	5,400	8,400	3,000	56%		21/05/2021
	00002		108			064	06/07/2021	420	4,020	3,600	857%		31/10/2021
	00001		257			021	24/05/2021	160	480	320	200%		25/06/2021
	00001		170			064	06/07/2021	21,736	34,488	12,752	59%		23/08/2021
	00001		242			064	06/07/2021	4,000	95,200	91,200	2280%		12/07/2021
	00001		166			064	06/07/2021	13,192	30,366	17,174	130%		20/09/2021
	00001		166			071	13/07/2021	41,410	45,222	3,812	9%		26/07/2021
	00001		166			064	06/07/2021	107,341	122,004	14,663	14%		19/07/2021
	00001		121			064	06/07/2021	6,384	10,990	4,606	72%		12/07/2021
	00001		242			021	24/05/2021	1,000	2,000	1,000	100%		26/05/2021
	00001		242			064	06/07/2021	4,074	6,531	2,457	60%		06/09/2021
	00001		170			064	06/07/2021	29,173	35,191	6,018	21%		30/08/2021
	00001		121			064	06/07/2021	23,760	31,320	7,560	32%		19/07/2021
	00001		121			064	06/07/2021	24,786	31,104	6,318	25%		19/07/2021
	00001		114			014	17/05/2021	6,048	12,960	6,912	114%		21/06/2021

Figure 95 - Early deliveries dashboard: PN Delivery Deviation tab

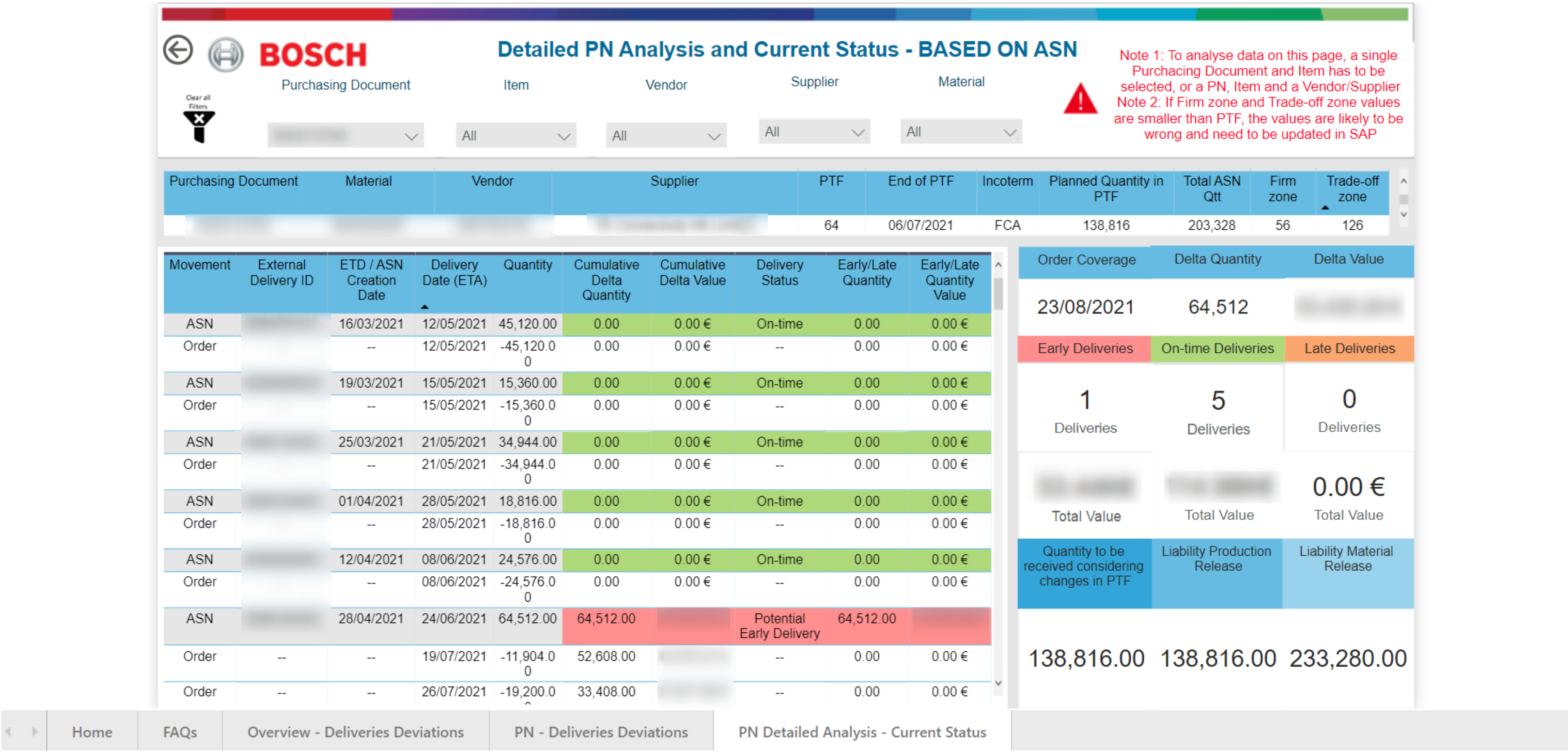


Figure 96 - Early deliveries dashboard: PN detailed analysis tab

APPENDIX 4 – DASHBOARD INSTRUCTION MANUAL

Manual de Análise de Envios em Avanço

Índice

Figure 97 - Page 1 of the instruction manual

1 Objetivo do manual

Este manual tem como principal objetivo servir de suporte à Análise de Envios em Avanço, definindo e detalhando o respetivo processo e a ferramenta de apoio ao mesmo.

2 Envios em Avanço

Um envio em avanço ocorre quando um fornecedor envia uma certa quantidade antes da data da encomenda planeada ou com excesso de quantidade relativamente à quantidade planeada. Quando o material chega a Braga e não tem nenhuma encomenda para que seja dada entrada, o mesmo é armazenado como material pendente.

Os envios em avanço têm um impacto significativo no desempenho da fábrica. Um dos principais impactos é nos stocks. Outro impacto tem a ver com a liquidez da empresa, já que um envio em avanço leva a que o pagamento dos materiais seja realizado mais cedo.

3 Dashboard de Deteção e Análise de Envios em Avanço

De modo a apoiar a decisão sobre como agir relativamente a um envio em avanço, LOS irá suportar-se no Dashboard de "Deliveries Deviations" (link: https://rb-powerbi.bosch.com/reports/powerbi/PBI/Production/Dashboard_Deliveries_Deviations_275259?rs:embed=true), cujas funcionalidades serão apresentadas neste capítulo.

O dashboard tem 5 separadores: Home, FAQs, Overview – Deliveries Deviations, PN – Deliveries Deviations e PN Detailed Analysis – Current Status.

Os dados do Dashboard são extraídos e atualizados diariamente do DALI, que é um sistema de armazenamento de dados do SAP.

3.1 Como funciona?

Para deteção dos desvios nos envios dos fornecedores, o dashboard compara as quantidades em trânsito segundo as ASNs com as encomendas em aberto no SAP.

Importante: o dashboard apenas apresenta fornecedores com ASN implementado (segundo informação no SAP).

Importante: São também excluídos fornecedores com VMI.

3.2 Home

A primeira página do Dashboard é o separador central e pode ser visto na Figura 1. Como é possível ver na imagem, estão destacadas várias funcionalidades, que se encontram numeradas:

1. Botão que permite ir para a página "**Overview – Deliveries Deviations**";
2. Botão que permite ir para a página "**PN – Deliveries Deviations**";
3. Botão que permite ir para a página "**PN Detailed Analysis – Current situation**";
4. Esta secção apresenta um conjunto de informações gerais relativamente ao dashboard;
5. Botão que permite ir para a página "**Frequently Asked Questions**";
6. Botão que permite reportar por email alguma falha possivelmente identificada no dashboard;
7. Menu que permite viajar entre separadores;

Figure 98 - Page 2 of the instruction manual

Figura 1- Separador principal

3.3 FAQs

O segundo separador contém algumas das perguntas mais frequentes e dúvidas que poderão surgir de forma recorrente e responde às mesmas.

Figura 2 - FAQs

3.4 Overview - Deliveries Deviations

Esta página apresenta:

- uma visão geral do estado atual dos envios em avanço;
- permite ver as peças mais críticas (com maior valor de envio em avanço)
- permite ver os fornecedores com maior valor de envios em avanço.

O separador pode ser encontrado em baixo com uma explicação das várias visualizações e gráficos (numeradas na imagem), bem como das possibilidades de interação.

Figure 99 - Page 3 of the instruction manual

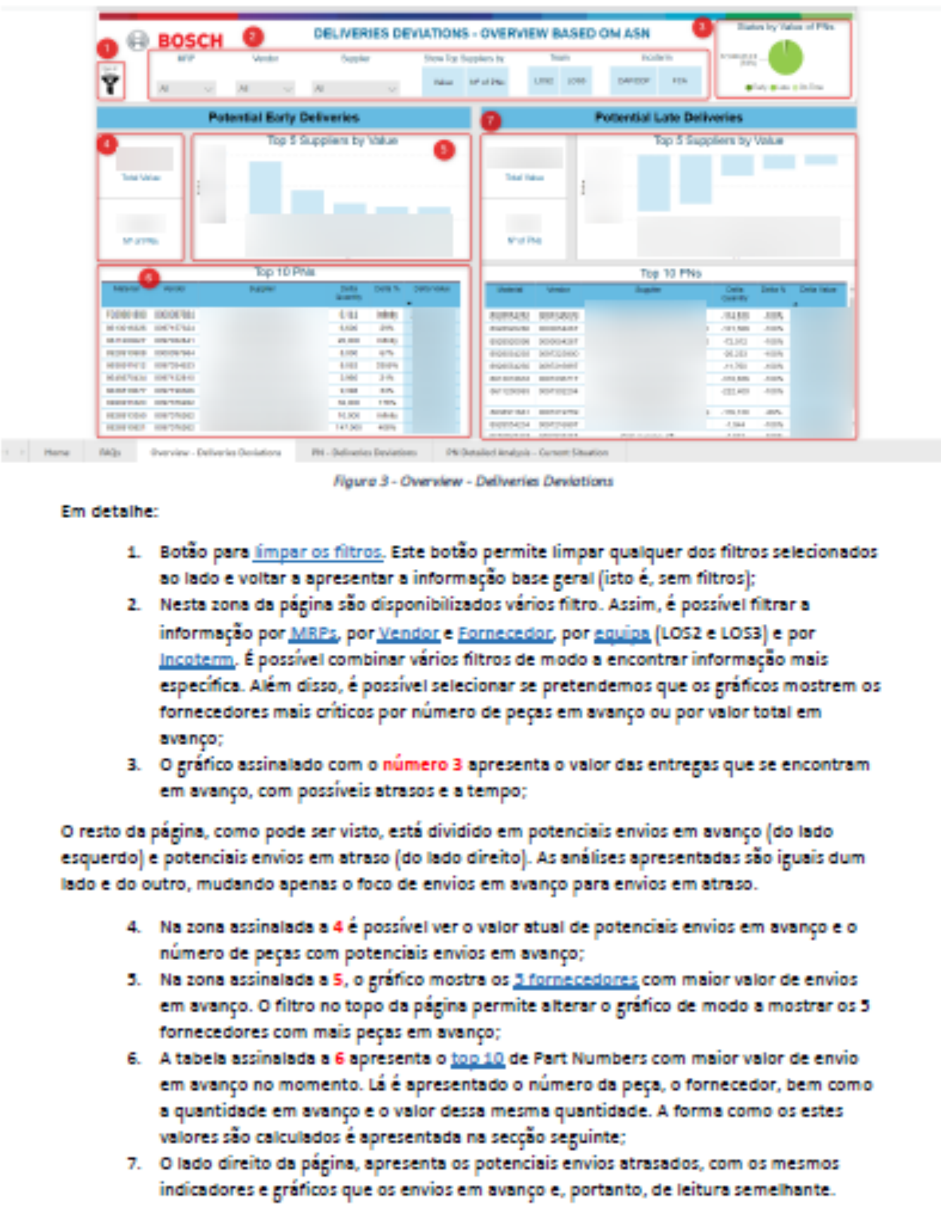


Figura 3 - Overview - Deliveries Deviations

Em detalhe:

1. Botão para limpar os filtros. Este botão permite limpar qualquer dos filtros selecionados ao lado e voltar a apresentar a informação base geral (isto é, sem filtros);
2. Nesta zona da página são disponibilizados vários filtro. Assim, é possível filtrar a informação por MRPs, por Vendor e Fornecedor, por equipa (LOS2 e LOS3) e por Incoterm. É possível combinar vários filtros de modo a encontrar informação mais específica. Além disso, é possível selecionar se pretendemos que os gráficos mostrem os fornecedores mais críticos por número de peças em avanço ou por valor total em avanço;
3. O gráfico assinalado com o número 3 apresenta o valor das entregas que se encontram em avanço, com possíveis atrasos e a tempo;

O resto da página, como pode ser visto, está dividido em potenciais envios em avanço (do lado esquerdo) e potenciais envios em atraso (do lado direito). As análises apresentadas são iguais dum lado e do outro, mudando apenas o foco de envios em avanço para envios em atraso.

4. Na zona assinalada a 4 é possível ver o valor atual de potenciais envios em avanço e o número de peças com potenciais envios em avanço;
5. Na zona assinalada a 5, o gráfico mostra os 5 fornecedores com maior valor de envios em avanço. O filtro no topo da página permite alterar o gráfico de modo a mostrar os 5 fornecedores com mais peças em avanço;
6. A tabela assinalada a 6 apresenta o top 10 de Part Numbers com maior valor de envio em avanço no momento. Lá é apresentado o número da peça, o fornecedor, bem como a quantidade em avanço e o valor dessa mesma quantidade. A forma como os estes valores são calculados é apresentada na secção seguinte;
7. O lado direito da página, apresenta os potenciais envios atrasados, com os mesmos indicadores e gráficos que os envios em avanço e, portanto, de leitura semelhante.

Figure 100 - Page 4 of the instruction manual

3.5 PN - Deliveries Deviations

Lista todas as peças com potenciais envios em avanço (e também com potenciais envios em atrasos).

1. O botão assinalado permite limpar os vários filtros que possam estar selecionados.

Figura 4 - PN -Deliveries Deviations

2. Conjunto de filtros que permitem aos utilizadores filtrar a tabela de modo a mostrar apenas a informação pedida. Assim, é possível filtrar a informação por MRPs, por Purchasing Document, por Vendor ou Supplier, por Material, por equipa e por Incoterm. Por exemplo, selecionando os MRPs 150 e 250, a tabela irá apenas mostrar as peças desses dois MRPs.

A tabela apresenta uma série de informações relativamente às várias peças com envios em avanço:

3. As informações apresentadas e assinaladas no **ponto 3** são as informações básicas das peças. Ali é indicado o Purchasing Document, o Item do Purchasing Document, o Part Number, o MRP aonde a peça está alocada, o Vendor, o nome do fornecedor e o valor de Planning Time Fence.
4. A coluna assinalada com o **ponto 4** apresenta a data de fim do Planning Time Fence. O valor do Planning Time Fence é a soma do tempo de processamento das encomendas com o tempo de trânsito. O campo "End of Planning Time Fence" é calculado somando à data do dia em que nos encontramos o valor do Planning Time Fence. É importante salientar que este valor poderá não ser igual ao que se encontra no SAP, visto que não tem em conta o Planning Calendar. No fundo, este valor indica que todas as encomendas com ETA até essa data já deviam estar em trânsito.
5. A coluna assinalada com o **ponto 5** "Planned Quantity in PTF" indica a quantidade planeada até à data indicada em "End of Planning Time Fence". No fundo, esta quantidade é a quantidade planeada que deveria estar em trânsito de modo a que chegue a Braga atempadamente.

Figure 101 - Page 6 of the instruction manual

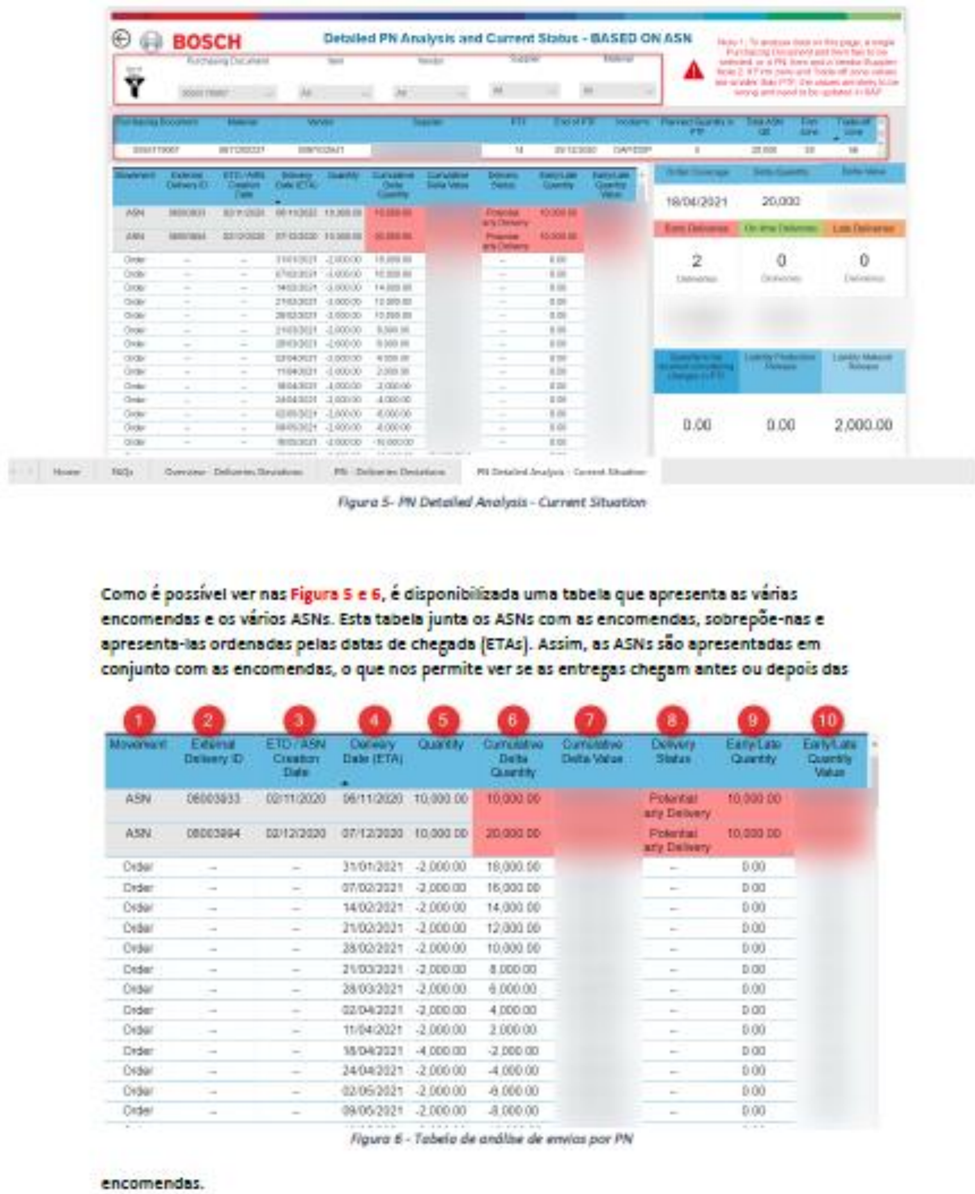


Figura 5- PN Detailed Analysis - Current Situation

Como é possível ver nas **Figura 5 e 6**, é disponibilizada uma tabela que apresenta as várias encomendas e os vários ASNs. Esta tabela junta os ASNs com as encomendas, sobrepõe-nas e apresenta-las ordenadas pelas datas de chegada (ETAs). Assim, as ASNs são apresentadas em conjunto com as encomendas, o que nos permite ver se as entregas chegam antes ou depois das

1 Movement	2 External Delivery ID	3 ETD / ASN Creation Date	4 Delivery Date (ETA)	5 Quantity	6 Cumulative Delta Quantity	7 Cumulative Delta Value	8 Delivery Status	9 Early/Late Quantity	10 Early/Late Quantity Value
ASN	08003933	02/11/2020	06/11/2020	10,000.00	10,000.00		Potential ary Delivery	10,000.00	
ASN	08003994	02/12/2020	07/12/2020	10,000.00	20,000.00		Potential ary Delivery	10,000.00	
Order	–	–	31/01/2021	-2,000.00	18,000.00		–	0.00	
Order	–	–	07/02/2021	-2,000.00	16,000.00		–	0.00	
Order	–	–	14/02/2021	-2,000.00	14,000.00		–	0.00	
Order	–	–	21/02/2021	-2,000.00	12,000.00		–	0.00	
Order	–	–	28/02/2021	-2,000.00	10,000.00		–	0.00	
Order	–	–	21/03/2021	-2,000.00	8,000.00		–	0.00	
Order	–	–	28/03/2021	-2,000.00	6,000.00		–	0.00	
Order	–	–	02/04/2021	-2,000.00	4,000.00		–	0.00	
Order	–	–	11/04/2021	-2,000.00	2,000.00		–	0.00	
Order	–	–	18/04/2021	-4,000.00	-2,000.00		–	0.00	
Order	–	–	24/04/2021	-2,000.00	-4,000.00		–	0.00	
Order	–	–	02/05/2021	-2,000.00	-6,000.00		–	0.00	
Order	–	–	09/05/2021	-2,000.00	-8,000.00		–	0.00	

Figura 6 - Tabela de análise de envios por PN

encomendas.

Figure 102 - Page 7 of the instruction manual

O objetivo desta tabela é facilitar ao utilizador a identificação de quais envios, que quantidades e que valor está a ser enviado em avanço.

Como é possível ver na figura 6, existem várias colunas na tabela com informação que facilite a análise:

1. A **primeira coluna** indica o que cada linha da tabela representa, isto é, se se trata duma encomenda ou duma ASN/entrega;
2. A **segunda coluna** indica o External Delivery ID das ASNs. No caso de uma encomenda, o campo aparece a branco;
3. A **terceira coluna** apresenta o ETD de uma ASN. Aquando da criação da ASN, o fornecedor deve indicar o ETD dessa entrega. Caso esse campo não seja preenchido, o SAP assume a data de criação da ASN como o ETD. No caso das encomendas, o ETD não é apresentado pois, devido a razões técnicas, não é possível a sua extração automática do sistema;
4. A coluna Delivery Date (ETA) indica a data de chegada de uma entrega no caso das ASNs e data da encomenda no caso das encomendas. É tendo em conta esta data que as várias linhas (ASNs e encomendas) são ordenadas;
5. A coluna Quantity indica, nos casos de ASNs, a quantidade em trânsito. No caso das encomendas, a coluna apresenta a quantidade encomendada, mas como valor negativo. De modo simples, as quantidades encomendadas aparecem com valores negativos, como se se tratassem de um consumo, enquanto que as ASNs aparecem com valor positivo, já que se tratam dum abastecimento. Isto é feito deste modo já que a entrada de uma entrega (ASN) em sistema, deve representar a baixa de uma encomenda;
6. O Cumulative Delta Quantity indica a quantidade de material do fornecedor estará em avanço ou em atraso em cada data, tendo em conta as entregas e encomendas de material. Este valor é calculado somando as quantidades das ASNs e encomendas ao longo do tempo;
7. A **coluna 7** indica qual o valor em avanço em cada data. No fundo indica o valor monetário do Cumulative Delta Quantity;
8. A coluna "Delivery Status" indica qual o estado duma entrega e duma encomenda, ou seja, se se encontra em avanço, em atraso ou a tempo. A coluna tem em conta o Cumulative Delta Quantity (bem como outras informações em background), o que lhe permite determinar se um envio está em avanço ou não. Caso um envio esteja em avanço, a tabela irá também assinalá-lo a vermelho. No caso de haver um envio em atraso, será assinalado a laranja, e no caso de estar a tempo, será assinalado a verde.
9. A **coluna 9** indica, por linha, dependendo do estado da entrega/encomenda, qual a quantidade que está em avanço ou em atraso. No exemplo da imagem podemos ver que indica que estão 10 000 peças em avanço em cada ASN.
10. A **coluna 10** indica qual o valor monetário da quantidade indicada na coluna 9.

Por fim, é possível ver do lado direito uma série de informações que são disponibilizados ao utilizador:

Figure 103 - Page 8 of the instruction manual

Figura 7 - Informação disponibilizada no canto inferior direito

As informações que são possíveis identificar na figura 7 são as seguintes:

1. O Order Coverage indica até que data as encomendas estão cobertas pela quantidade em trânsito ou em que data se entraria em rotura caso não surjam mais entregas;
2. Já falado na secção 3.4, indica qual a quantidade que está em trânsito que se encontra a mais em relação à quantidade planeada;
3. Já falado na secção 3.4, indica qual o valor da quantidade que está em trânsito que se encontra a mais em relação à quantidade planeada;
4. Este ponto indica qual o número de entregas (ASNs) que se encontram em avanço, e qual o valor em avanço dessas entregas.
5. Este ponto indica qual o número de entregas (ASNs) que se encontram a tempo, e qual o valor total das quantidades dessas entregas.
6. Este ponto indica qual o número de encomendas que se encontram atrasadas, e qual o valor total das quantidades dessas encomendas.
7. O "Quantity to be received considering changes in PTF" é um valor que permite ao planeador perceber qual quantidade que tem obrigação de receber do fornecedor, tendo em conta possíveis alterações às encomendas que tenham sido feitas dentro do Planning Time Fence. Para esta análise são consideradas as releases do período de PTF mais 7 dias a contar para trás do dia de hoje. O Dashboard analisa os períodos de Planning Time Fence nas várias releases e verifica se ficou por receber alguma quantidade. Assim sendo, o valor indicado neste ponto diz ao utilizador qual a quantidade que a Bosch tem obrigação de receber da parte do fornecedor.
8. A "Liability Production Release" indica qual a Production Liability que a Bosch tem para com o fornecedor. É preciso ter em conta que são utilizadas apenas as releases dos últimos 6 meses e o valor de Production Release (Firm zone) é o que está mantido no sistema, pelo que é importante verificar na tabela se o mesmo se encontra atualizado.
9. A "Liability Material Release" indica qual a Material Liability (incluindo Production Liability) que a Bosch tem para com o fornecedor. É preciso ter em conta que são

Figure 104 - Page 9 of the instruction manual

utilizadas apenas as releases dos últimos 6 meses e o valor de Material Release (Trade-off zone) é o que está mantido no sistema, pelo que é importante verificar na tabela se o mesmo se encontra atualizado.

4 Processo de Análise de Envios em Avanço

O Dashboard tem de ser consultado quinzenalmente e de forma proactiva pelos planeadores de modo a detetar potenciais envios em avanço. Como já foi possível ver, o Dashboard deteta também potenciais envios em atraso.

A cada duas semanas, serão selecionadas pelos Team Leaders e Section Manager de LOS as peças mais críticas em termos de envios em avanço e que devem ser analisadas.

O processo de seleção de peças, bem como o processo de análise das mesmas, encontra-se documentado de seguida.

4.1 Seleção das Peças a analisar

Critérios:

1. No Point CIP semanal, serão selecionadas as peças mais críticas, consultando o separador "PN - Deliveries Deviations":

Figura 8 - Tabela com PNs com Envios em Avanço

2. Nas semanas ímpares serão selecionadas para análise as peças elétricas (LOS2) e nas semanas pares as peças mecânicas (LOS3). As peças podem ser filtradas no filtro assinaladas no ponto 1.

3. Os critérios a ter em conta para seleção das peças são o valor em avanço ("Delta Value") e a cobertura ("Order Coverage"). Assim, devem ser selecionadas todas as peças que correspondam a um dos seguintes critérios:
   a. Delta Value > 5 000 €
   b. Order Coverage > Data atual + 2 PTF

Figure 105 - Page 10 of the instruction manual

c. Análise do TOP 5 por equipa

Podem ser escolhidas outras peças de fornecedores críticos, tanto pelo planeador, como pelos coordenadores.

4. Após estarem selecionadas as peças, as mesmas devem ser comunicadas aos planeadores da maneira que os Team Leaders acharem mais conveniente (email, teamboard, ficheiro excel, etc).

4.2 Análise dos envios do fornecedor

Após receber a indicação das peças sinalizadas, ou por iniciativa própria, o planeador deve proceder à análise dos envios da mesma. Para tal, irá abrir o separador "PN Detailed Analysis - Current Status":

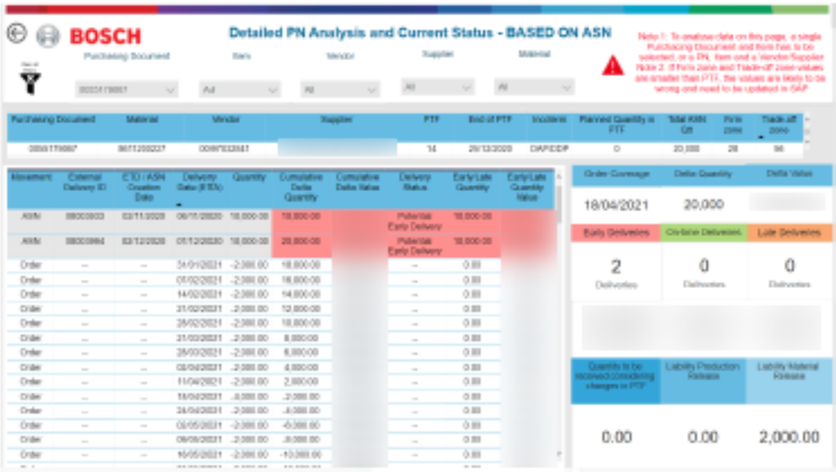


Figura 8- PN Detailed Analysis - Current Status

Na tabela, os planeadores devem analisar os vários envios (sinalizados como ASN):

1. A primeira coisa que o planeador deve fazer é identificar quais os envios que está potencialmente em avanço. Esses envios estão sinalizados a vermelho e com o status de "Potential Early Delivery", como é possível ver na **Figura 9**:

Figure 106 - Page 11 of the instruction manual

Movement	External Delivery ID	ETD / ASN Creation Date	Delivery Date (ETA)	Quantity	Cumulative Delta Quantity	Cumulative Delta Value	Delivery Status	Early/Late Quantity	Early/Late Quantity Value
ASN	08003933	02/11/2020	06/11/2020	10,000.00	10,000.00		Potential Early Delivery	10,000.00	
ASN	08003994	02/12/2020	07/12/2020	10,000.00	20,000.00		Potential Early Delivery	10,000.00	
Order	--	--	31/01/2021	-2,000.00	18,000.00		--	0.00	
Order	--	--	07/02/2021	-2,000.00	16,000.00		--	0.00	
Order	--	--	14/02/2021	-2,000.00	14,000.00		--	0.00	
Order	--	--	21/02/2021	-2,000.00	12,000.00		--	0.00	
Order	--	--	28/02/2021	-2,000.00	10,000.00		--	0.00	
Order	--	--	21/03/2021	-2,000.00	8,000.00		--	0.00	
Order	--	--	28/03/2021	-2,000.00	6,000.00		--	0.00	
Order	--	--	02/04/2021	-2,000.00	4,000.00		--	0.00	
Order	--	--	11/04/2021	-2,000.00	2,000.00		--	0.00	
Order	--	--	18/04/2021	-4,000.00	-2,000.00		--	0.00	
Order	--	--	24/04/2021	-2,000.00	-4,000.00		--	0.00	
Order	--	--	02/05/2021	-2,000.00	-6,000.00		--	0.00	
Order	--	--	09/05/2021	-2,000.00	-8,000.00		--	0.00	
Order	--	--	16/05/2021	-2,000.00	-10,000.00		--	0.00	

Figura 9 - Tabela com Envios e Encomendas

2. O planeador deve estimar quanto tempo o envio chega em avanço, olhando para a coluna "Delivery Date (ETA)" (assinalada com o **ponto 1** na **Figura 10**). É importante salientar, que como nem sempre é possível associar uma ASN a uma só encomenda, não é possível calcular automaticamente quanto tempo esta chega em avanço. Assim, o planeador deve procurar ver que encomendas o envio em questão cobre e verificar a data. Os critérios para definir se a o envio tem um impacto significativo são:

   a) Valor da quantidade em avanço >= 1 000 euros
   b) Cobertura da entrega / tempo de avanço >= 2 semanas

   Pelo exemplo da **Figura 9**, a primeira ASN de 10 000 peças cobre as encomendas até ao dia 28/02/2021, num total de 5 encomendas de 2 000 unidades cada. Podemos concluir que chegou com uma antecedência superior a 2 meses. Possui um valor em avanço de cerca de 40 000 euros, pelo que se pode concluir que o envio tem um impacto significativo. A mesma lógica se aplica à segunda ASN/envio. Caso a peça cumpra os critérios, o planeador deve prosseguir com a análise, caso contrário, deve concluir aqui.

   É preciso salientar que o planeador deve ter em conta a situação geral da peça, ou seja, verificar se existem alguns envios em atraso e até situações de quebra de material. Nestes casos o planeador deve avaliar a situação no sentido de ver se fará sentido reclamar um envio em avanço ao fornecedor e alinhar com o seu Team Leader.

3. De seguida e de modo a perceber se deve avançar com uma reclamação ao fornecedor, o planeador deve perceber o porquê de o envio estar a ser assinalado pelo dashboard. Assim a primeira coisa a verificar é se foram feitas ao fornecedor encomendas que não estejam colocadas no sistema (por exemplo, encomendas de transportes especiais, risk orders, last time buys, etc). Caso se verifiquem que existem encomendas, o planeador deve colocar as mesmas no sistema corretamente e concluir aqui a análise. Se não

Figure 107 - Page 12 of the instruction manual

houver nenhum acordo com o fornecedor relativo a encomendas não colocadas no sistema, o planeador deve avançar para o próximo ponto.

4. Por fim, o planeador deve verificar se houve alterações de encomendas dentro do Planning Time Fence que possam ter sido feitas. Para tal o planeador deve verificar a visualização assinalada na Figura 10:

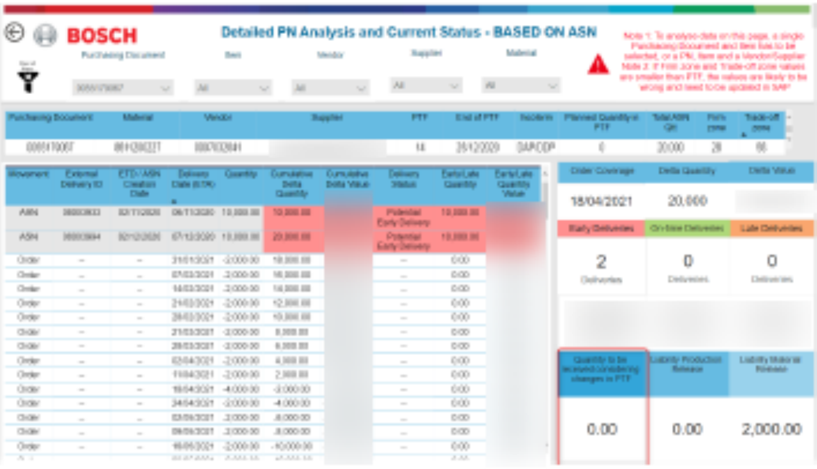


Figura 10 - PN Detailed Analysis - Current Status

Como explicado na secção 3.5, esta visualização calcula qual a quantidade que a Bosch tem que receber do fornecedor, tendo em conta as Releases no período de tempo Planning Time Fence + 7 dias, a contar para trás da data de hoje. Neste exemplo, a peça tem um PTF de 14 dias, o que significa que são analisadas as releases dos últimos 21 dias e é verificado que quantidades foram cortadas dentro do Planning Time Fence (Frozen Zone). Neste caso, o valor é 0, o que significa que o fornecedor não tem motivo para enviar estas quantidades em avanço. Neste caso, o planeador avança com o pedido de reclamação ao fornecedor (Q2).

Caso este valor seja maior que a quantidade atualmente planeada, o planeador deve verificar se a quantidade a receber é igual ou maior ao valor em trânsito. Caso seja, não deve reclamar. Caso este valor seja igual à quantidade atualmente planeada, significa que não há alterações dentro do Planning Time Fence e deve-se reclamar os envios identificados no ponto 2. Neste exemplo em particular, seriam reclamados dois envios em avanço de 10 000 peças cada.

Numa situação em que o planeador não avance com uma reclamação, pode contactar o fornecedor no sentido de o alertar e tentar uniformizar os envios de modo a que fiquem o mais regularizados possível.

Sempre que o planeador avançar com uma reclamação ou um contacto ao fornecedor, deve tirar um print <u>apenas da tabela</u> e guardar o mesmo para ser enviado ao fornecedor nas

Figure 108 - Page 13 of the instruction manual

comunicações. Isto deve ser feito no momento já que os dados vão sendo atualizados diariamente e o estado das peças pode mudar.

Figure 109 - Page 14 of the instruction manual

APPENDIX 5 – EARLY DELIVERIES DATA CLEANSING AND PREPARATION (DATA WORKFLOW)

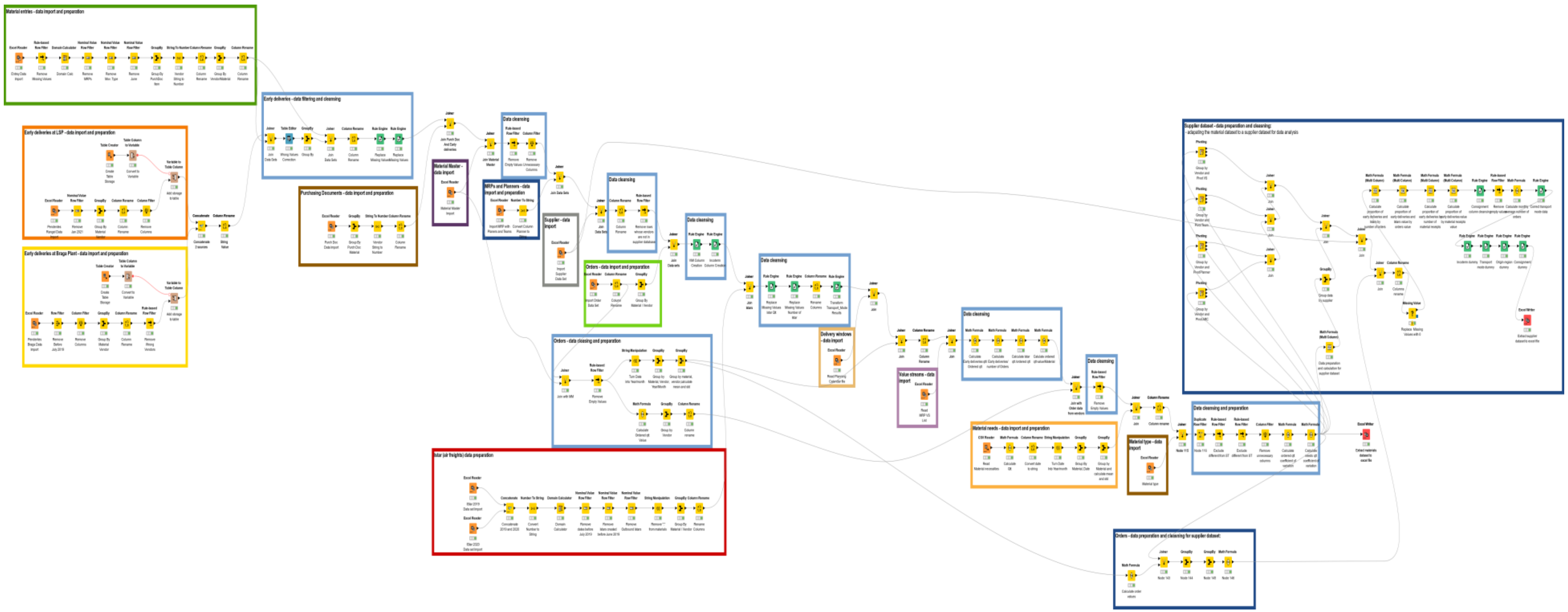


Figure 110 - Early deliveries data workflow

Appendix 6 – R code used for analysis of early deliveries performance and potential risk factors

```r
library(readxl)
Suppliers_dataset <- read_excel("Desktop/Análise de Envios em avanço/Projeto Envios em avanço/Risk Analysis/Suppliers_dataset.xlsx")
library(lattice)
plot(y=Suppliers_dataset$`Number of Early Deliveries`,x=Suppliers_dataset$`Transport Mode Dummy`,col=cols)
Suppliers_dataset<-Suppliers_dataset[Suppliers_dataset$`Number of Early Deliveries / Number of orders`<=1]
#distribution of early deliveries performance
hist( Suppliers_dataset$`Number of Early Deliveries / Number of orders`, ##histogram distribution of supplier according to origin
      breaks = 60,
      col = "lightblue",
      main = "Early deliveries performance",
      xlab = "Early deliveries / number of orders",
      xlim = c(0,1), ylim = c(0,300),
      cex.main = 1.7, cex.lab = 1.4, las = 1,
      labels = TRUE)

#Boxplot transport mode
Suppliers_dataset$`Transport Mode`<-reorder(Suppliers_dataset$`Transport Mode`,
                                            Suppliers_dataset$`Number of Early Deliveries / Number of orders`,median)
boxplot(`Number of Early Deliveries / Number of orders` ~ `Transport Mode`, Suppliers_dataset,
        horizontal = TRUE,
        ylab="",
        col = "lightblue",
        ylim = c(0,1),
        cex.main = 1.7,
        cex.lab = 1.4,
        cex.axis = 1.4,
        las = 1,
        outline=TRUE,
        main="Early deliveries performance distribution by tranport mode")
```

Figure 111 - R code used to create histograms and boxplot

```r
library(readxl)
library(ggplot2)
library(writexl)
library(readr)
Suppliers_dataset <- read_excel("Desktop/Análise de Envios em avanço/Projeto Envios em avanço/Risk Analysis/Suppliers_dataset.xlsx")

#analysis of average number of orders
sup<-Suppliers_dataset[Suppliers_dataset$`Number of Early Deliveries / Number of orders`>=0,c(1:60)]
y<-sup$`Number of Early Deliveries / Number of orders`
x<-sup$`Monthly average number of orders`
plot(x,y)

theme_set(theme_bw())
data<-as.data.frame(cbind(x,y))
legend_title <- "Origin of dispatch"
sup$`Origin Region (dispatch)`<-as.factor(sup$`Origin Region (dispatch)`)
p<-ggplot(data=sup,aes(x=x,y=y,color =sup$`Origin Region (dispatch)`))
  +geom_point(cex=2)+xlab("Monthly average number of orders")+ylab("Early deliveries / number of orders")
  +xlim(0,75)+ylim(0,0.55)+scale_color_manual(legend_title,values=c("red", "blue", "green"))
l2<-p+geom_smooth(colour="blue",width=1,se=T);l2 #usando local regression (loess) para adapatação da curva de tendência
l2+theme(
  axis.title.x = element_text(color="black", size=10, face="bold"),
  axis.title.y = element_text(color="black", size=10, face="bold")
)
```

Figure 112 - R code used for plots and trend analysis