Development of an end-to-end Supply Chain monitoring and visualization tool in an e-commerce business

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Abstract

Standardization and consolidation of processes are essential for a company to continue its growth in a sustainable way. The company where this project was developed - Farfetch - has grown immensely in the last years, accompanying the personal luxury segment's growth tendency, and it is vital that internal processes and information flows advance and expand methodically.

Supply Chain plays a very important role in every business; but in a marketplace, which is dependent on the partners' performance, Supply Chain becomes an even more decisive character. To have optimized supply chain processes will - surely - lead to operational advantages and cost reduction. However, in order to optimize a process it is necessary to have visibility on it, and to measure, monitor and report a specific set of metrics capable of describing in an easy, intuitive and accurate way, the condition of that same process.

A Supply Chain Management System has the enhancement of customer satisfaction as ultimate goal, as this is what creates value for the company. For that, it has to both monitor all critical activities and be capable of acting if something falls off the targets. A powerful tool to achieve this target is the use of dashboards, which aim at presenting solely the necessary metrics to control the process in an effective and efficient way.

The problem addressed in this project is precisely the development of a consolidated, unanimous dashboard, which serves as a control tower to monitor the health of the end-to-end supply chain process. In fact, there are currently several reporting routines scattered across multiple teams and all meaningful data is dispersed across numerous locations in the company's database, in a very unstructured way.

The company's rising customer-centric mindset puts an extra emphasis and interest on metrics, which evaluate the supply chain process from a customer point a view, that is, illustrating the real impact the company's operations have on clients' experience and, consequently, willingness to buy again with Farfetch.

The developed tool enhanced the visibility on the entire supply chain process, through weekly and monthly monitoring of the most significant business' metrics. An intuitive and analytical visualization tool was developed, so that the metrics assessing performance can be available to everyone who needs it.

A KPI needs a yardstick to be compared with, so efforts towards the dynamic definition of reference lines assessing the number of orders being processed, which is the central part of all operations, have been initiated.

Resumo

A uniformização e consolidação de processos são essenciais para fundamentar o crescimento de uma empresa de uma forma sustentável. A empresa onde este projeto foi desenvolvidao, a Farfetch, cresceu de forma muito acentuada nos últimos anos - acompanhando a tendência de crescimento do setor de luxo - e o progresso metódico de processos internos e fluxos de informação é de elevada importância para que este comportamento se mantenha no futuro.

A cadeia de abastecimento tem um papel significativo em qualquer negócio, alcançando uma posição ainda mais elevada num *marketplace*, que depende fortemente do desempenho dos parceiros. A sua otimização levará, seguramente, a vantagens operacionais e a redução de custos. Porém, estas vantagens só serão possíveis após ter visibilidade sobre os processos envolvidos, pelo que a medida, a monitorização e a comunicação de métricas internas que os descrevam de forma simples, intuitiva e precisa são necessárias.

Um sistema de avaliação da cadeia de abastecimento tem como objetivo final aumentar a satisfação dos clientes. Para tal, o sistema deve, simultaneamente, monitorizar todas as atividades críticas e ser capaz de atuar corretivamente se necessário. Os *dashboards* são uma ferramenta poderosa para tal são 'dashboards', que, tal como os painéis de controlo dos carros, pretendem apresentar somente as métricas necessárias para controlar o processo em causa de forma eficiente e eficaz.

Este projeto trata do desenvolvimento de um *dashboard* unitário, global e completo, que tem o intuito de constituir uma torre de controlo para a monitorização do estado de toda a cadeia de abastecimento. A empresa possui, de momento, múltiplas rotinas de comunicação de métricas dispersas pelas várias equipas que contituem o departamento de Operações, que utilizam dados recolhidos de várias fontes, de forma desestruturada.

A empresa dá acrescido valor a métricas que descrevam o funcionamento da cadeia de abastecimento do ponto de vista do cliente, avaliando-o de acordo com o impacto real dos processos na experiência do cliente e, consequentemente, na sua vontade de voltar a usar os serviços da empresa.

A ferramenta desenvolvida no âmbito deste projeto trouxe visibilidade a todo o processo da cadeia de abastecimento, através da monitorização semanal e mensal de um conjuunto de métricas selecionadas de forma criteriosa. A ferramenta foi construída de forma intuitiva, de modo a que o referido conjunto de métricas esteja disponível para consulta de todos os interessados, e é adaptável às necessidades do utilizador.

Ainda no âmbito do projeto foi desenvolvida uma ferramenta que permite, semanalmente, comparar o estado da cadeia de abastecimento com um intervalo de referência obtido através dos resultados da semana anterior.

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"If you can't explain it simply, you don't understand it well enough."

Albert Einstein

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Acronyms and Symbols

3PL	Third-Party Logistics
APAC	Asia Pacific
API	Application Programming Interface
ATV	Actual Transaction Value
AUNZ	Australia and New Zealand
AWB	AirWay Bill
BaU	Business as Usual
CIS	Commonwealth of Independent States
CR	China Region
CS	Customer Service
EAM	Enterprise Evaluation Methodology
EDD	Estimated Delivery Date
FA	Forecast Accuracy
FxFF	Fulfillment by Farfetch
GMV	Gross Merchandise Value
JP	Japan
KPI	Key Performance Indicator
LATAM	Latin America
MAPE	Mean Absolute Percent Error
NPS	Net Promoter Score
NS	No Stock
O2D	Order To Delivery
POF	Perfect Order Fulfillment
PS	Partner Service
RoW	Rest of the World
SaA	Suggest an Alternative
SCA	Supply Chain Analytics
SCM	Supply Chain Management
SCPMS	Supply Chain Performance Measurement System
SLA	Service Level Agreement
SoS	Speed of Sending
SQL	Structured Query Language
TT	Transit Time
USA	United States of America
WI	Wrong Item

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Chapter 1

Introduction

This project was developed in the scope of the Masters in Mechanical Engineering in Faculdade de Engenharia da Universidade do Porto and performed in corporate context at Farfetch.

Fashion has always played a significant role in the evolution of society: from being a key social element of the Romans to boosting international trade during the years of industrialization (Okonkwo, 2007), the acquisition and possession of luxury goods have always been a way of showing personality, individualism and social and financial status.

Veblen (1899), a hundred years ago, in his Conspicuous Consumption Theory, commented on people's disposition and willingness to pay an increased price for prestigious, unique products to display prominent social status.

A few years later, Coco Chanel defined luxury as 'the opposite to vulgarity' and quoted that 'luxury is a necessity that begins where necessity ends.' (Okonkwo, 2007).

Last year, online sales of personal luxury goods accounted for 8% of the €254 billion global luxury market, or about €20 billion, according to Achille et al. (2018). The same author also states that 'that is up five-fold from 2009 and we expect online luxury sales to more than triple by 2025, to about €74 billion'.

This already billion-dollar and growing industry is the core of Farfetch's business and the desire of constantly exceeding customers' expectations is the company's goal.

1.1 Farfetch

Founded by José Neves in 2008, Farfetch is an online luxury fashion marketplace, which connects more than 1200 partners - luxury boutiques, brands and warehouses - to millions of customers all over the world, on a single website. 11 years after its launch, Farfetch has partners in 49 countries, and has clients in more than 190 countries. It has offices in 13 different cities and is growing over 50% every year, having generated a record Gross Merchandise Value (GMV) in 2018 (Halliday, 2019), being since 2017 the first Portuguese company valued more than 1 billion dollars. In October 2018 the firm entered the New York stock exchange and in the same year revenue rose by 56% and the number of placed orders increased 58%. Farfetch also owns British renowned boutique 'Browns' and American footwear brand 'Stadium Goods'.

In 2019 Farfetch already announced the acquisition of JD.com's luxury platform Toplife to enable the gateway to the China market and the partnership with Harrods, to create and manage the department's e-commerce platform (Suen, 2019).

Farfetch's aim is to offer the luxury goods customers a unique, creative, excellence service. The company's business model is what distinguishes it from its competitors and is the one of a marketplace: it doesn't hold any stock or have its own transportation system. The partners, who, due to their presence on the website, have a visibility and accessibility they wouldn't have otherwise, sell directly from their own stock points to the clients. The client only knows which partner he/she is buying from at the time of delivery, as all the information flow passes through and is managed by Farfetch. In order to guarantee the desired service levels, the company controls the whole process, from content creation through delivery to the client's house to the post-sales customer service. The delivery service is outsourced from third-party logistics partners (3PL), which charge Farfetch a shipping fee. The price payed by the customers includes the item's price, Farfetch's margin and the shipping fee.

The business model is, however, associated with higher complexity and numerous challenges, such as the risk of stock out, the dependency on the partner's performance, and the complexity of delivery (as there are a great number of possible routes).

Farfetch is organized in the following departments: Global Operations, Product, Communications, Technology, Finance, Strategy and Commercial.

The Global Operations Department is responsible for all activities related with daily e-commerce and consists of several teams, as shown in Figure 1.1.

The Creative Operations team is responsible for everything that has to do with Farfetch's content production. It ensures, among others, products' photographing and availability online.

The Logistics team manages all order shipment related activities, including products' return processes.

The Customer Excellence team is the bridge linking the company to partners and clients, through Customer Service (CS) and Partner Service (PS) teams. CS representatives help customers with their complaints and questions, both pre and post order, and PS supports boutiques and brands on operational issues.

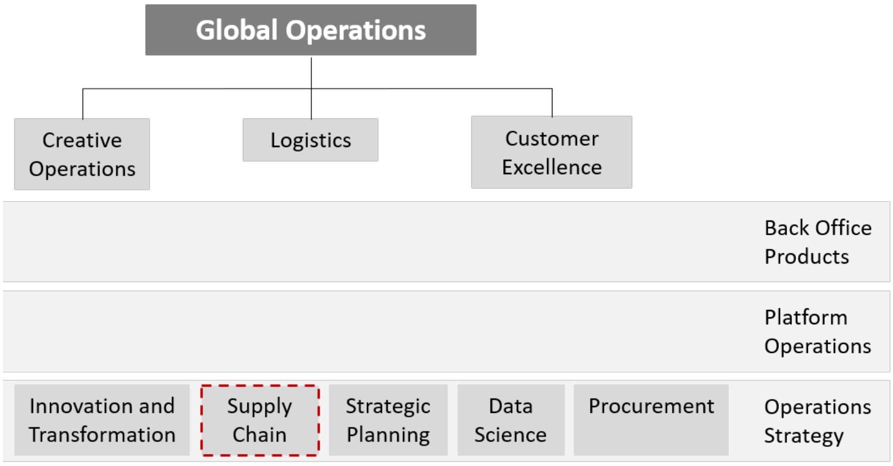


Figure 1.1: Global Operations' structure

Back Office Products, Platform Operations and Operations Strategy are cross functional teams, which support the other teams and work on the continuous improvement of processes and, ultimately, of customer experience.

This project was developed in the Supply Chain team, which is a part of Operations Strategy. The Supply Chain team's responsibility is to ensure the proper order processing flow and to control and monitor partners' performance. All packaging issues are the Supply Chain's responsibility, as well.

A core principle of Farfetch is customer-centricity: the main focus of the company is to improve customer experience. Objectives, targets and rewards are aligned with this strategy and this is what makes Farfetch a truly data-driven and innovative company. A customer-centric culture is 'unanimously accepted as the driver of future growth and development' (Banovic-Curguz and Ilisevic, 2018). This key consideration will guide the entire project.

1.2 Current Problem and Project Scope

Farfetch has grown very rapidly and its structure evolved enormously. To ensure a healthy growth, it is of extreme importance to guarantee the proper flow of the supply chain processes, which will surely impact customers' experience, satisfaction, and even retention.

Currently there is very low monitoring of the whole Supply Chain - the existing routines are spread out over the multiple Operations teams, which use their own KPIs. There is no standardization, nor a unified dashboard or scorecard that presents the current state of the Supply Chain in an easy, concise, consistent and flexible way. The current reporting methods are manual, exhausting and have a low performance due to the huge amount of data.

The above mentioned issues justify the urge to define a control tower including every KPI that shall be measured and monitored, in order to gain visibility on the entire system's performance on a weekly basis. The monitoring of the end-to-end supply chain's performance implies the comparison with dynamic targets and this will lead to the identification of possible pain points. From that moment, where all the process's performance is visible and measurable, it will be possible to react fast and in a more effective way to eventual problems.

1.3 Project Goals

The current project has the intent of constructing a concise, intuitive and flexible dashboard, which acts as a control tower for monitoring the health of the company's end-to-end supply chain system. The project defined goals are:

- Map every process belonging to the supply chain process;
- Build a scalable and robust dataset, to serve as the source for all necessary analyses;
- Create, rearrange and adapt already existent and new KPIs to fit the dashboard's purpose and the company's goal;
- Develop and promote a customer-centric approach to the system's monitoring;
- Select a relevant set of KPIs to evaluate the system's performance;
- Compare current performance with targets or benchmarks;
- Gain visibility on the real customers' experience, in order to improve it;
- Automate current processes of KPI reporting.

The dashboard is to be used by a wide range of people and teams, from business analysts to directors. Thus, it must on the one hand give a high-level perspective of the whole process and on the other hand permit a detailed view of each operation.

Alignment with the company's customer-centric mindset is a crucial feature for the dashboard to effectively be used.

1.4 Methodology

The dashboard development procedure was adapted from the one suggested by Vilarinho et al. (2018).

This project was divided in four major steps, namely the construction of the comprehensive dataset, the definition and calculation of new metrics, the development of the dashboard(s) and the iteration of the obtained solution, aiming at meeting all requirements.

In order to understand the functioning of the Supply Chain process, the whole order processing was examined.

Afterwards, it was investigated which actions have an impact on customer satisfaction, and a metric to measure it was selected. Some KPIs were already being used by the company, but others had to be created. The company's gradual move to customer-centricity made it necessary to adapt already existing metrics, as well.

In order to build a dashboard that will be used by multiple teams, overcoming the problem of having many teams calculating their KPIs in a somehow autonomous way, the teams Partner Service, Customer Service, Fulfillment Operations, Delivery and Partner Success were involved in the dashboards' development process.

After having completed the dashboard views, the task of defining benchmarks for the pipeline status was focused on.

Subsequently, after the dashboard's implementation and test phase, a presentation was held for several managers, in order for them to inform their teams of the existence and usability of the dashboard.

1.5 Dissertation Structure

This project is divided in six chapters, as following:

Chapter 1 - Introduction to the present work, including the projects' scope and goals, as well as used methodologies;

Chapter 2 - Theoretical background, scientifically supporting the decisions and assumptions made during the elaboration of the project;

Chapter 3 - Detailed description of Farfetch's business and of the Supply Chain's current process and visibility;

Chapter 4 - Exposition of the steps executed during the current project;

Chapter 5 - Presentation of the final results, as well as listing of the effects of the project;

Chapter 6 - Conclusion of the current work, summarizing all the improvements and changes due to the implementation of the proposed solution, as well as definition of next steps.

For confidentiality reasons, all values shown in tables or graphs in this project are fictional. In some cases values are real, but the graph's axis was multiplied by a random factor.

Chapter 2

Theoretical Background

In this chapter, the performed literature review is presented.

2.1 Luxury Goods

Luxury is a Latin word with old and still debated roots. It does not descend from 'lux' (light and enlightenment); instead, it is closer to 'luxatio', which means 'a disruption, an excess of' (Kapferer, 2015).

Ko et al. (2017) state luxury is a relative concept, and peoples' perception of what is 'luxury' has varied over time. According to Okonkwo (2007), luxury is not a product nor an object, nor even a lifestyle. It is rather an identity, a philosophy and a culture. Thus, the purchase of luxury goods intends to simultaneously fulfill the consumers' functional, symbolic and hedonic needs such as ego or self-esteem, the desire of projecting and affirming a self-image, the necessity of social status reinforcement or the desire of individualization (Okonkwo, 2009).

The literary review performed by Ko et al. (2017) identifies multiple key theories aiming to explain the motivation for luxury consumption: the self-concept theory, the social comparison theory, the extended-self theory, the theory of uniqueness and the conspicuous consumption.

2.2 Who is the Luxury consumer?

In the luxury business more than in others, the consumer is king, and if a brand wants to be successful, it has to focus on its consumers, understand them and continuously deliver them the best experiences.

Luxury consumers can be segmented into multiple categories according to their financial status or fashion insights (Chen and Zhang, 2011; Shen et al., 2017), but a distinction regarding consumers' mindset and behavior is more illustrative. There are the *traditional luxury consumers*, who look for traditional and exclusive brands and the *new luxury consumers*, who are rather attracted by the offered shopping experience than by the brands' names. The latter ones prefer experience over materialism, are highly sophisticated, literate and savvy and know exactly want they want. Their choices of luxury products are based more on an understanding of their own style needs and less on the 'brand-name' factor (Okonkwo, 2007). These consumers will be loyal to those brands whose service quality level doesn't cease to constantly exceed their expectations and fulfill their needs of personal and social identity (Okonkwo, 2007).

Contrasting with the traditional view that what drives consumers to buy luxury products is their uniqueness and rarity, Ko et al. (2017) enunciate a survey performed in 2012, which showed evidence that nowadays many brands are able to mass-market luxury items. Nevertheless, the question of how can luxury brands manage growth worldwide while remaining rare enough to be desirable, is yet to be answered.

This shift in the luxury consumers' mindset is pushing luxury brands to redefine what they deliver to customers, and how they deliver it (D'Arpizio et al., 2017). To do that, they rely more and more on digital technologies, such as Artificial Intelligence and Big Data, which are helping them to redesign customer engagement techniques through data analytics (Arienti, 2018).

2.3 Luxury E-Commerce - The Experience of Shopping Online

Although 'there was no love at first sight between luxury and Internet' (Heine and Berghaus, 2014), due to the luxury sector's fear of losing its aura (Okonkwo, 2007), as soon as consumers accepted the Internet as a convenient platform for luxury goods shopping (Chen and Zhang, 2011), brands had to quickly adopt this new channel.

The luxury sector's initial apprehension and resistance towards the digital world contrasts with the usual avant-gardism and innovation that characterize it (Okonkwo, 2009). An explanation is the back then existing idea that the Internet was a place for discounted, damaged or counterfeit goods. However, consumers are in fact willing to buy luxury products online, and at 'undiscounted' prices (Dauriz et al., 2014; Castillan et al., 2017), and in recent years the growth of online luxury sales has overcome the one of overall sales of luxury goods. The evolution of worldwide online personal luxury goods market sales in the past 15 years is depicted in Figure 2.1.

Achille et al. (2018) forecast that the volume of online luxury sales will reach 19% of all the transactions of this sector by 2025, amounting to €74 billion.

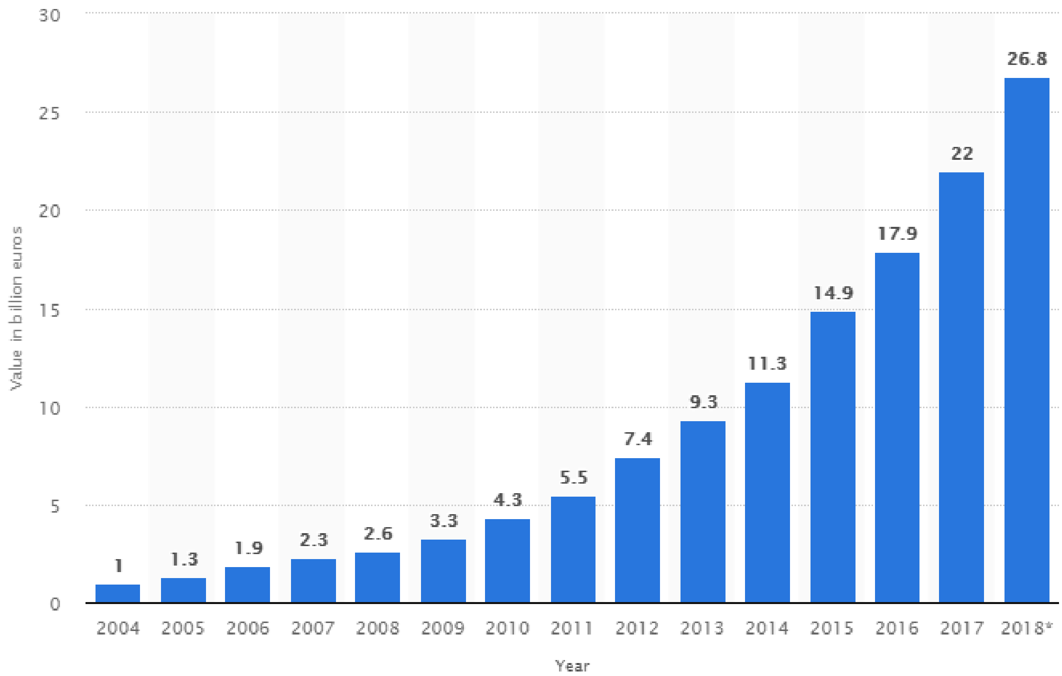


Figure 2.1: Global Online Luxury Sales in the past 15 years (Statista, 2019)

By the same year it is expected that about 40% of luxury customers will be today's 16 to 35 year olds - the mentioned *new luxury consumers* -, compared to only 27% in 2016 (D'Arpizio et al., 2017). The new generations' tech savviness is forcing brands to invest in the digital market and to use social media to engage with customers (Arienti, 2018).

Although bringing along challenges and risks, the internet provides a unique opportunity to access the huge market of the online consumer population.

According to Achille et al. (2018), in 2018 about 80% of luxury sales were 'digitally influenced' - during the luxury purchase journey customers come in touch with at least one digital interface, either seeking advice on social media or buying the luxury item online or subsequently posting about their purchases.

Due to the undeniable growth and acceptance of Internet, luxury brands are being forced to switch their mindset from rigidity to reception of and adaption to a constantly evolving world (Okonkwo, 2009). An alliance between luxury and technology is quickly emerging among the most forward-looking brands, which will enable rapid response to shifts in demand and customer needs, cost reduction and the ability to quickly interpret and use customer data (Achille et al., 2018). The same authors also agree that, however, e-retail doesn't replace the physical retailers - it is rather a complementary sales channel for offline activities, and, therefore, online and offline strategies should not be separated (Castillan et al., 2017).

A company's level of online interaction with the customer is gradually decreasing from company-driven (owned channels) to consumer-driven (social channels) and third-party platforms (paid channels). According to Achille et al. (2018), the digital shopper is increasingly seeking a multibrand experience and, therefore, it might be effective for brands to establish partnerships with multi-brand retailers or marketplaces online (Dauriz et al., 2014), which hold the competencies required for the digital transformation.

A study by Liu et al. (2013), in line with Chen and Zhang (2011), shows there are differences between online and in-store shopping behaviors of luxury consumers. These authors conclude that online shoppers are worried about convenience, price, product availability and online trust, whereas in-store shoppers have higher consideration for issues like aesthetic appeal, store trust, shopping experience and customer service.

2.4 Customer-centric Platform Thinking

A platform business creates 'value primarily by enabling direct interactions between two or more participant groups' (Uenlue, 2017), as seller and buyer, service provider and service seeker or content creator and consumer.

On many digital networks the cost of serving an additional user is negligible, which makes a business inherently easier to scale up (Zhu and Lansiti, 2019). The long-term success of a product or service depends heavily on the health, defensibility and dominance of the ecosystem in which it operates. In these kind of businesses the employees don't deliver the product or service - instead they just design and oversee an automated, algorithm-driven operation - so the structure of the network influences the platform business's ability to sustain its scale. This form of IT setup enables companies to innovate, experiment, fail, learn and scale very quickly (Bossert and Desmet, 2019).

A big threat to platforms which capture value directly from matching and by facilitating transactions is disintermediation - network members, suppliers and clients, don't need the hub anymore, bypassing it and connecting directly. As a way to avoid this phenomenon, platforms try to enhance the value of conducting business on them (Zhu and Lansiti, 2019).

Hereof, the more a network is fragmented into local clusters, the more isolated these clusters are from each other and the more vulnerable the business is to challenges. When the network effect weakens, so does the market position (Zhu and Lansiti, 2019). Figure 2.2 depicts two distinct network clusters of modern platforms, with two completely different network formats.

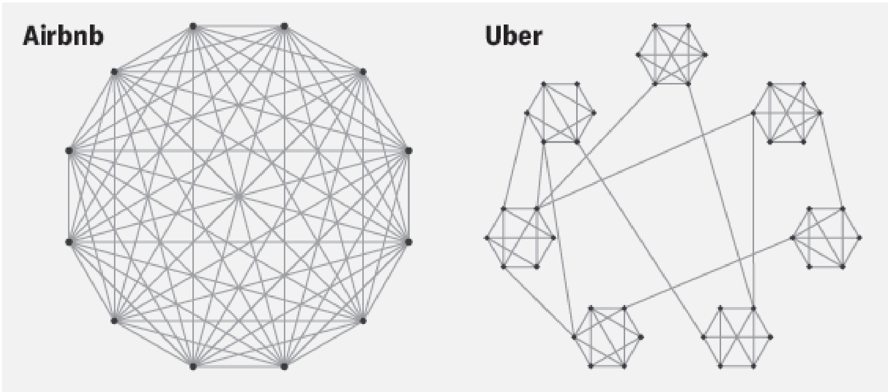


Figure 2.2: Global and local platform users' networks (Zhu and Lansiti, 2019)

Delivering innovative solutions and keeping up with customers' expectations requires an innovation driven culture with customer value at its center. Platform-based companies do this by organizing their business around a set of modular 'platforms', which are logical clusters of activities and associated technologies that deliver a specific business goal. Platforms focus on delivering business solutions to serve internal or external clients and enable a great flexibility, as they can be managed and run as independent services, be swapped in an out and assembled in different ways (Bossert and Desmet, 2019).

There are two core digital structures - digital platforms and ecosystems. Digital platforms allow a range of digital products on top of them, such as advertising or marketplaces. Ecosystems, on the other hand, often start with a consumer need for a service, and the ecosystem provides the match between supply and demand (Bughin and Catlin, 2019).

2.5 Supply Chain Performance Management Systems

Supply chain performance is one of the most critical issues in various industries, as supply chains are involved in the entire product life cycle (Balfaqih et al., 2016). To monitor and evaluate the supply chain's overall performance is a complex task (Cai et al., 2009), resulting in general benefits such as assessing and controlling progress, highlighting accomplishments, improving understanding of key processes, identifying potential problems and providing insight about possible improvement actions (Lima-Junior and Carpinetti, 2017).

Performance measurement and management have become essential for organizations to survive in the competitive business environment (Elgazzar et al., 2018) and specifically, improving supply chain performance has become imperative for gaining competitive advantages for companies (Cai et al., 2009). A functioning supply chain is the key to guarantee service quality and to achieve customer satisfaction, which will lead to customers' increased willingness to pay premium for the value-added experience (Shen, 2015). Operational and supply chain strategy should therefore be aligned with customer strategy (Maestrini et al., 2017).

A Supply Chain's strategy and practices are shaped by the firm's business model. Business requirements are not static along the company's life cycle - for this reason, when the business model evolves, supply chain strategy has to be renewed or adapted, too, in order to maintain competitive advantage. The KPIs' definition and calculation must evolve accordingly to the system requirements. Therefore, a KPI measurement set shall be provided with suitable mechanisms that allow KPI evolution processes to be accomplished easily and effectively (Robinson and Hsieh, 2016; Domínguez et al., 2019).

The literature review performed by Robinson and Hsieh (2016) identified four distinct types of supply chain strategy, namely *efficient* (aim is creating highest cost-efficiency), *risk-hedging* (aim is minimizing risks of supply disruption), *responsive* (aim is being responsive and flexible to the changing customers' needs) and *agile* (aim is being responsive to the shifts in customers' demands on the front-end while minimizing risks of supply disruptions on the back-end).

The goal of a supply chain performance management system (SCPMS) is to support the implementation of the supply chain strategy and the fulfillment of its objectives (Maestrini et al., 2017). As a supply chain management system often involves monitoring multiple processes and relationships, which don't belong to the company's sphere of influence, the same author defines a SCPMS as 'a set of metrics used to quantify the efficiency and effectiveness of supply chain processes and relationships, spanning multiple organizational functions and multiple firms and enabling supply chain orchestration'. A SCPMS should be based on the company's strategic objectives and consists of diverse processes, such as measure identification, target definition, planning, communication, monitoring, reporting and feedback (Cai et al., 2009). The impact of supply chain performance on the company's overall performance should also be included (Elgazzar et al., 2018).

The critical review of published research on SCPMS conducted by these authors identified four main possible concepts behind them: process focus, prioritization of performance measures, integration of different dimensions and causality between variables investigation. As supply chain performance is not a one-dimensional concept, a particular SCPMS may belong to more than one of the referred categories.

The supply chain process may be, generally, divided into three stages, according to Stanley et al. (2018) - source, make and deliver. Regarding the delivery process, the same authors state that last-mile delivery is especially important for customers, as it offers convenience and flexibility, and that is why same-day and on-demand-delivery services are becoming more and more important.

The same author state there is no single optimal supply chain performance measurement tool, as each company's supply chain is different. In order to be effective the framework must:

- capture the essence of organizational performance;
- be aligned with the company's strategy and current objectives;

- enable target setting;
- show both financial and non-financial measures;
- be reliable;
- enable aggregation and prioritization;
- facilitate integration;
- be simple and easy to use;
- enable fast feedback and continuous improvement.

In opposition, the most important criticisms addressed to supply chain management systems and the main causes why their potential is not always reached, are the lack of connection with strategy, the excessive number of metrics and the inconsistency in performance measurement (Elgazzar et al., 2018).

The same authors allege that the performance system must also be able to evaluate the current supply chain performance from different perspectives.

2.6 E-Supply Chains

Businesses have now fewer boundaries than ever before, due to globalization, the increased use of outsourcing, the development of information technology (IT) and the increased demands of integration (Balfaqih et al., 2016; Arzu Akyuz and Erman Erkan, 2010). These novelties in the business environment require adequate performance measures and metrics to enhance supply chain efficiency (Balfaqih et al., 2016).

Examples of web-based retail platforms, connecting sellers to consumers, are Farfetch.com, Alibaba.com, Amazon.com, eBay.com or Taobao.com (Shen, 2015). Time is a decisive criterion for service quality, as customers are increasingly depending on and expecting a fast response. The same authors also affirm that customer loyalty is significantly related to 'fulfillment and responsiveness'. An analysis performed by Park and Hong (2014) considers the hypothesis of the market demand being not only influenced by the retail price and service level, but also by the service time.

Supply chain management (of online marketplaces) starts with a decisive forecasting system, whose aim is to avoid or at least minimize the mismatch between supply and demand (Shen, 2015). Flexibility and channel coordination are enormous assets, too, as they permit a more prompt response to the various fluctuations in supply and demand and are, therefore, determinant for the service's performance improvement.

Nowadays large amounts of digital information exist on virtually any topic of interest to a business (McAfee et al., 2012). The proper use of Big Data - cleaning, organizing and extracting useful information from it (Radermacher, 2018) - leads a company to decision-making on the basis of evidence and rigor rather than intuition, allowing better predictions, smarter decisions and more effective interventions (Radermacher, 2018; Peral et al., 2017; Fernández et al., 2015).

However, big data's power does not erase the need for vision or human insight. In tackling big data, computers have an advantage over people with their ability to consume huge amounts of information, but are less effective in having the judgment or ability to understand the implications of made decisions (Mukherjee, 2016).

A survey performed by McAfee et al. (2012) concluded that 'data-driven decisions tend to be better decisions', which is sustained by Moore (2017).

2.7 KPI Selection for Correctly Monitoring a Business Process

According to Kaplan and Norton (1992), decision makers cannot manage what they cannot measure. To continuously measure, monitor and evaluate a specific, dynamic set of metrics is the key to supply chain processes' optimization in terms of efficiency and effectiveness (Cai et al., 2009). Vilarinho et al. (2018) affirm that the main challenge for successful continuous improvement is to develop a sustainable infrastructure that implements, promotes and coordinates metrics' monitoring.

Maestrini et al. (2017) define a metric as a verifiable performance measure (stated in either qualitative or quantitative terms) that assesses a happening through a reference or target value, and that is associated with consequences of being on, below or above target. Expanding this definition, Domínguez et al. (2019) make use of Parmenter's definition of Key Performance Indicators as 'a set of measures focusing on those aspects of organizational performance that are the most critical for the current and future success of the organization'. Therefore, when defining KPIs, one should always have the end result in mind (McNeeney, 2005), namely the achievement of strategic goals.

KPIs can be used with the purpose of evaluating the (past or present) performance of a monitored system, or to predict the future behavior of the system (Domínguez et al., 2019). In modern companies, Business Intelligence (BI) technologies provide historic, existing and predictive sights of business operation (Kumar and Belwal, 2018).

Having an effective and relevant KPI selection is essential in today's competitive business environment, but modern supply chain systems are filled with too many individual measures, which can be counterproductive (Domínguez et al., 2019). To select the most adequate key performance indicators is considered a multi-objective problem (Chorfi et al., 2015), involving a broad number of aspects (Domínguez et al., 2019). An adequate KPI selection should involve considerations in terms of the KPIs' suitability for the company's strategic objectives, profile and current life cycle situation, as well as the time frame (Muntean et al., 2016) and effective metrics result in defining significant action and improvement, rather than simply monitoring performance (Kumar and Belwal, 2018).

There are several guidelines proposed in order to assist the effective definition of a set of KPIs and a widely used one is the SMART (**S**imple, **M**easurable, **A**ttainable, **R**ealistic and **T**ime related) criteria (Chorfi et al., 2015; McNeeney, 2005). The particular circumstances of each company make it necessary to adapt and customize general KPI definitions, tailoring them to deal with the company's specific situation and needs (Domínguez et al., 2019).

A powerful method for selecting the most adequate and significant KPIs for a company is the Enterprise Analysis Model (EAM), as suggested by Kaganski et al. (2017). It consists of a questionnaire, to be filled by several people with different positions within the organization, with the goal of getting insight on which data is relevant and is necessary to be collected and monitored. After analyzing and ranking the answers according to a significance index (based on the collaborators' role in decision making), it is easier to select the KPIs to be implemented.

Regarding KPI selection, Ahmed et al. (2017) consider machine learning as a powerful tool to establish rules to identify the best KPIs for a business, through determination of a KPI score, establishment of correlations and pairwise comparison between each considered KPI.

According to Domínguez et al., 2019 the KPI's features, summarized in Figure 2.3, are:

- hardness refers to a KPI's subjective or objective nature;
- calculation rule is the calculation's specific formula;
- value type specifies the type of data in which the KPI is expressed, as well as its unit of measure;
- filter has to do with conditions that may accompany the KPI and play the role of filters;
- frequency refers to the periodicity with which the KPI is calculated;
- target depicts the KPI's objective and may be presented in the form of an absolute value or a range;
- status options are divisions of the KPI's range of values in certain intervals with particular meanings;
- source refers to the entities and databases that are necessary to compute a KPI;
- computation refers to the way a KPI is computed;
- measured aspects indicate which business level the indicator measures (duration, cost, quality,...).

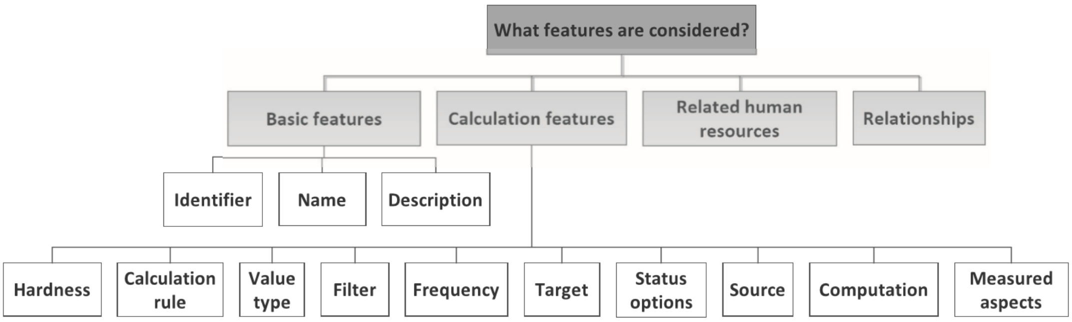


Figure 2.3: Features to be considered in the specification of KPIs (Domínguez et al., 2019)

Referring to the human resources related to a particular KPI, the same authors identify the roles of the *owner*, the *responsible* and the *interested*. The people or departments involved in the development and usage of a KPI are referred by the ISO 22400 standard as the KPI's 'audience'.

After having defined and calculated adequate key performance indicators, the critical ones have to be identified and correction actions prioritized, which can be as defying as the KPI definition (Cai et al., 2009).

It is critical for performance measurement systems and related criteria to be updated, evaluated and refined constantly (Cai et al., 2009) and automation provides both reliability and time savings collecting the data. According to McNeeney (2005), 'without a central location to collect, store and report KPI data, it can be extremely difficult to manage metrics unified around a strategy map'. Changes in the organization's objectives may be reflected as changes in a particular indicator's target (Muntean et al., 2016).

2.8 Data Visualization Techniques

The major goal of data visualization techniques is to provide users with a qualitative and easy understanding of the information contents (Kumar and Belwal, 2018), permitting an efficient interpretation of data and, consequently, data-driven decision-making (Moore, 2017).

The process of extracting useful information from large, complex data sets is called big data mining. One of the main challenges associated with it is, precisely, visualization, as analytic results have no meaning when devoid of context and when not displayed in a way users can understand and utilize (Peral et al., 2017; Moore, 2017; Yigitbasioglu and Velcu, 2012). Therefore, when representing a metric, it is necessary to understand what context it needs to be meaningful, and provide it.

Visual methods always imply the risk of possible misunderstanding of visual information, which may lead to wrong conclusions (Sedrakyan et al., 2019; Vilarinho et al., 2018). In order to avoid this and to pass the right and most useful information to decision-makers in an effective way, certain visualization principles deserve a cautious forethought. One of the pillars of visualization techniques is the perception theory, having been developed over the past years.

Sedrakyan et al. (2019) identify three types of feedback a visualization method may provide: *summative* (understand habits, make comparisons and track progresses towards goals), *real-time* and *predictive feedback*. Each desired output is best accomplished recurring to a particular visualization method. The same author presents a set of visualization metrics - effectiveness, expressiveness, readability and interactivity - aiming to help choosing the most suitable visualization for a given data set.

Data Visualization is, due to its complexity, regarded as an important skill for today's data-centric, analytic jobs (Ryan et al., 2019).

One important data visualization technique is dashboards, whose name comes from vehicle dashboards, where only the few metrics the driver needs to know are provided. Dashboards must be concise, accurate, simple and intuitive to use (Yigitbasioglu and Velcu, 2012) and deliver a comprehensive awareness of current performance (Kumar and Belwal, 2018; Peral et al., 2017), by comparing it with a target or benchmark.

In recent years dashboards have evolved from the sole purpose of monitoring performance to more advanced analytic purposes (Velcu-Laitinen and Yigitbasioglu, 2012). As such, they are expected to collect, summarize and present information from multiple sources, so that the user can see at once how various performance indicators are performing (Yigitbasioglu and Velcu, 2012). Dashboards are data-driven support systems, providing comprehensive information of the trends and historical information about the company's KPIs in a synthesized way, acting as triggers for further analyses, if needed. In the same authors' words, regarding data the dashboards only provide 'the tip of the iceberg'.

Vilarinho et al. (2018) classify the possible purposes of a dashboard as following:

- to monitor critical activities and processes (using metrics that set off alerts when performance falls off established goals);
- to analyze the causes of problems (by exploiting relevant and timely provided information through several perspectives and levels of detail);
- to manage people and processes to improve decisions.

The identification of the dashboard's purpose enables adjustment of its features, to guarantee that stakeholders' needs are met.

The goal of a dashboard is to improve perception, and not complicate, hinder or bias it (Yigitbasioglu and Velcu, 2012), which makes it necessary to deliberate on some aspects during the design stage. There is a balance between dashboards' visual complexity and usability, as excessive features and information might actually have an adverse impact on the decision makers' capability to decide. The utility of the information is also a crucial point: the amount of presented data has to be limited, in order to maintain objectiveness, relevancy and focus and to not overwhelm the audience with unnecessary information (Moore, 2017; Archambault et al., 2015).

Dashboards' usability - and reliability - also depend on the quality of the data used to produce it, defined in matters of accuracy, completeness, currency and consistency. Data is accurate when it is correct, unambiguous, objective, meaningful and believable. Its completeness depends on the users' demands and its currency refers to being up-to-date. Consistency involves the absence of conflicts between two data sets and to the reliability of the data during a longer period of user experience (Moore, 2017; Velcu-Laitinen and Yigitbasioglu, 2012; McNeeney, 2005).

User acceptance also defines the usability of a dashboard (Domínguez et al., 2019). Therefore, a viable attribute to include is a built-in user feedback mechanism, which will enable future refining, improving and adjusting visualizations based on the users' needs (Sedrakyan et al., 2019).

Dashboards include functional and visual features, and the desired effect might only be achieved if both are coordinated. Examples of functional features are real-time notifications and alerts, drill-down capabilities, scenario analysis, presentation flexibility and external benchmarking (Velcu-Laitinen and Yigitbasioglu, 2012). The study performed by these authors reveals there is a positive correlation between drill-down features and productivity.

The data-ink ratio has been proposed by Yigitbasioglu and Velcu (2012), which measures the proportion of ink used to represent data to the total ink used to print. The goal of this measure is to avoid redundant visual information. The use of gridlines and labels as visual aids leads to unbiased decision making (by avoiding visual illusions in graphs), but, simultaneously, contents which distract the users from the key dashboard information - 'chart junk' (Archambault et al., 2015) - should be avoided (Vilarinho et al., 2018). Visual alerts can help identify performance indicators that went out of range an need immediate attention (Yigitbasioglu and Velcu, 2012). The use of colors has to be cautious and strategical, too, - analogous, complimentary or monochromatic palettes maximize the visualization's effectiveness - and 3D objects must be avoided, as they may lead to confusion and hinder comparisons (Archambault et al., 2015).

The same authors also illustrate that different types of information require different visualization formats in order to be effective. While graphs are more useful for tasks that require identifying and understanding relationships, making forecasts, comparisons and pattern recognition, tables are more suitable for tasks that require extracting and/or comparing specific values. In order to avoid misinterpretation of graphs, it is important that they are well labelled (Yigitbasioglu and Velcu, 2012).

Sedrakyan et al. (2019) expand this idea and outline the most appropriate visualization techniques for each aim: columns or lines are most indicated to show trends; comparisons are best established through area, bars, bullets, columns, lines or scatter; relationships are visualized through lines or scatter; bars, box plots or columns picture distributions and compositions are to be illustrated by donuts, pies, stacked bars or stacked columns. At this point, the theory of perception suggests that people are much more sensitive to lengths than to angles, which is why bars are more indicated than pie charts.

As the business' and company's environment is dynamic, literature advises to go with flexible dashboard solutions that enable easy upgrades (Yigitbasioglu and Velcu, 2012), as well as allowing a certain degree of customization (Sedrakyan et al., 2019; Vilarinho et al., 2018).

Chapter 3

Problem Description

In this chapter particular processes and designations, which are crucial to a comprehensive understanding of Farfetch's business model, are presented.

3.1 Ordering Process

Farfetch's partners are either boutiques, brands or warehouses. Each of them has specific characteristics, targets and strategical relevance, but they all will be designated as *partners* along this project. Whenever needed, further clarification will be provided.

When a client places an order on Farfetch website, the order is allocated to a specific partner, which has the ordered product in stock. When there are several partners in this condition, an algorithm allocates the order considering the product's cost (extra shipping costs), the expected time to delivery at the client's house and, lastly, the partners' past performance. The item's price is always the first criterion for partner allocation.

A customer only knows which Farfetch partner fulfilled the order at the time of delivery - reason why Farfetch is a marketplace, and not an e-retailer. If the order contains more than one product, it is possible that they are shipped from different partners, which means that they will probably not arrive at the client's house at the same moment, too. In this case, it is necessary to understand the difference between Portal Order, Boutique Order and Product Order. Figure 3.1 illustrates the difference.

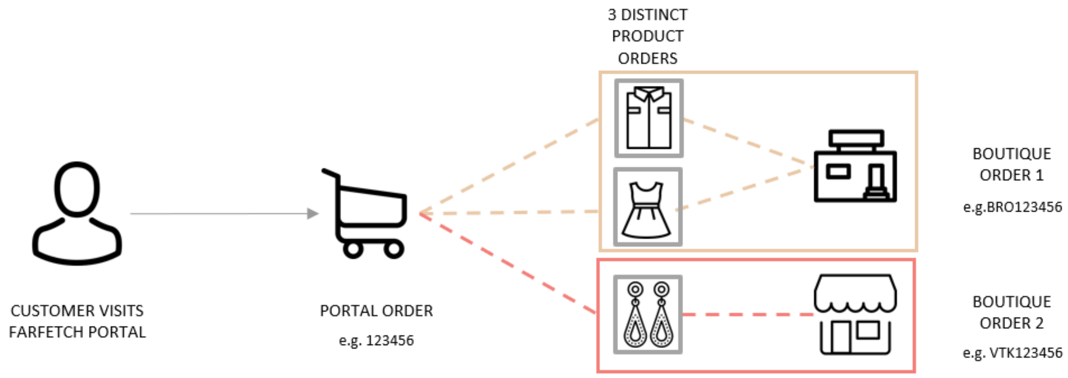


Figure 3.1: Difference between portal orders and boutique orders

Th example shown in Figure 3.1. presents an order of three products made by a single customer. Two of the products are shipped from the same boutique, while the third is shipped from a different one.

In terms of identification, the Boutique Order Code is the Portal Order Code preceded by the boutique's initials. Each product order corresponds to a single product, belonging to a boutique order. In Farfetch's databases, a portal order corresponds to an OrderSiteID, a boutique order is identified by an OrderCodeID and a product order is referred to by an OrderLineID.

Once an order is placed by a customer, an Estimated Delivery Date (EDD) is automatically sent by e-mail, together with the order's code and receipt, as a range of days. This estimation takes only the shipping option (DHL Express, DHL Standard, UPS Express, UPS Standard,...) into consideration and ignores the shipping route, except for the cases where the shipping country is China or Brazil, due to operational constraints entering these two countries.

If a client places an order, which will be fulfilled by a partner in Milan, and wants to have one item shipped to his residence in France and the other to his residence in New Zealand, the displayed EDD will be the same. There is an ongoing project, which intends to include routing in the EDD calculation.

At the same time, the placed order starts its flow through six different steps (see Figure 3.2) it necessarily goes through before arriving at the customer's house. Farfetch is responsible for the steps associated with the order control, while the ones involving physical activities, are the partners' responsibility.

Exceptions can be created by partners in steps 1, 3 and 5, reporting unexpected situations that may occur during the ordering process, in an attempt to not prejudice the partners' indicators if something happens that delays the ordering process, but that is not their fault. Exceptions result in the order being on hold until the exception is solved. The procedure to solve and analyze exceptions involves several teams, including the Supply Chain team, which ultimately determines if an exception is valid. In that case, the partners' indicators are subsequently recalculated subtracting to the Speed of Sending the time interval it took to solve the exception. There are 13 possible exceptions.

The current order processing flow is shown in Figure 3.2.

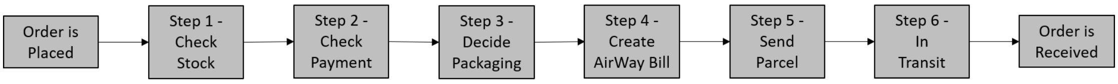


Figure 3.2: Process Ordering Flow

A detailed description of each step is provided next. For better comprehension, the process swim lane of each step is presented in Appendix A.

3.1.1 Step 1 - Check Stock

The first stage of the order processing is the partner's stock confirmation. Most of the company's partners are boutiques which, besides selling their luxury goods online, also sell them offline. Therefore, and being related to not instantaneous stock synchronization, a 'No Stock' situation may occur. In this case the lack of stock on the demanded product is communicated to Farfetch, which checks if other partners have the product. If this is the case, a so called *Item Swap* is carried out with the client never knowing about it. A child order is created and the parent one is canceled.

In the opposite situation, if the ordered product is not available at all, Farfetch contacts the customer, explains the situation, suggests similar products (by partner's suggestion) and, eventually, performs a refund, depending on the client's demands.

Price increases due to 'Item Swap' are held by Farfetch and the ones due to 'Suggest an Alternative' (see subchapter 3.2.2) are sustained by the partner. Due to the partners' greater costs, alternative suggestions are unusual.

3.1.2 Step 2 - Check Payment

The Fraud Team is responsible for step 2, and, although it theoretically comes after step 1, it is usually performed in parallel with its predecessor. As soon as the order is placed, it is automatically checked if the customer is in the so called Blacklist, the White List or none of them. White List customers are those who have a confirmed, secure and reliable payment source; Blacklist customers are those associated with a distrustful one.

Blacklist clients' orders are automatically cancelled and white list ones' automatically approved; the remaining customers are evaluated and depending on their suspicion they are approved or go through 'Under Investigation' process. In some cases, it can be necessary to directly contact the customer to request a Proof of Billing by phone. When the order is not reliable, the fraud analysts cancel the order, reporting the reason for cancellation and adding the suspect to the Black List.

3.1.3 Step 3 - Decide Packaging

In the third step, partners use an internal application to consult Farfetch's package recommendation and select the package(s) to be used for each order.

It is also partners' responsibility to guarantee an unique and luxury customer experience, which includes a perfect unboxing experience. Thus, the package shall be adequate for the product it contains, and, eventually, include customized details.

Farfetch provides advice about the boxes partners shall use to pack each range of products. However, partners are not obliged to follow these instructions and can set a new box if it is required, creating an exception called 'Product Packaging Issue'.

All packaging boxes are supplied by an external company. Based on the sales forecasts provided by Farfetch, the partners are responsible for ordering their own packaging stock.

3.1.4 Step 4 - Create AirWay Bill

The fourth step consists on the creation of the shipping labels, which are indispensable for couriers to identify the delivery destination. An AirWay Bill is automatically created, unless there is any problem with the shipping information or legal restrictions. These have to be handled by the Delivery team. Historically, 95% of the orders take less than 2 hours to pass Step 4.

3.1.5 Step 5 - Send Parcel

When the shipping label is ready, the order is pushed forward to Step 5 to be collected by the courier. If the partner does not have a scheduled, daily pick up, Farfetch's system automatically books it, usually for the next day.

During this process, partners can, again, create exceptions in order to complain or inform about something that is not right (i.e. Courier failed to pick up the parcel).

Once the courier scans the package, the order is moved to Step 6.

3.1.6 Step 6 - Order is Sent

The sixth and last step starts when the courier collects the box and comprehends the stage when the parcel is in transit, ending when the order is delivered to the client.

Once the parcel is scanned, the company sends a confirmation email to the customer, specifying the time the partner spent to process the order and the estimated time that will be spent by the courier to deliver the order. The carrier charges Farfetch a value based on the distance travelled and the volume/weight of the order.

The courier scans the order at the delivery point, too, and this log is afterwards used by Farfetch to evaluate overall performance.

3.1.7 Return Process

If a client is not satisfied with the purchased article, it is possible to return it within the next 14 days and get a refund. The most typical reasons to return are sizing, fitting or quality issues, description misguidance, the shipment of a wrong item or the customer having changed his or her mind. Several clients also buy the same article in more than one size to try them at home and return the one(s) that don't fit.

The client can initiate the return process via phone call or through the website. The courier pick up is scheduled with the client, the courier scans the package at pick up time, and it is scanned again when it arrives at the partner. Afterwards, there is a 48h period where the boutique has the chance to accept or contest the return - the latter case may occur due to a late return, a damaged item or others. If the partner accepts the return, the refund is at its cost; otherwise, the refund is at Farfetch's cost and the item is sent to Farfetch, to be either resold at a symbolic value or given to charity.

3.2 Key Performance Indicators

The Supply Chain team uses a set of five main KPIs to measure the system's performance. A description of each is provided in the next subchapters.

3.2.1 Speed of Sending (SoS)

Speed of Sending is a metric that measures the total time elapsed between an order's creation and the package's scan by the courier at the end of Step 5.

This description corresponds to SoS Gross. However, as there are events that are not controlled by the partners, such as the existence of weekends or holidays and the accomplishment of steps 2 and 4, SoS Gross is not always a fair performance indicator. Therefore, SoS Net is also evaluated, representing the time elapsed between the order's creation and the package's scan at the end of step 5, less the time spent in all steps that are not controlled by the boutique (Step 2 and Step 4), the time spent on weekends and holidays and the time where the order may be held by factors external to the partner (approved exceptions).

The calculation formulae are presented in the following equations.

$$\textit{SoS Gross} = \textit{Courier Scan Date - Order Creation Date} \tag{3.1}$$

$$\begin{aligned}\textit{SoS Net} = \textit{Time Spent in Steps 1,3 and 5 - Time Spent on Weekends}\\ \textit{and Holidays - Time Spent on Hold}\end{aligned} \tag{3.2}$$

The percentage of orders sent in less than 1 day (24h) and in less than 2 days (48h) are also measured by the company, and global targets are defined for both metrics - the Service Level Agreements (SLAs). The partners' performance is evaluated considering, among others, their SoS Less Than 2 Days (see subchapter 3.6.2).

3.2.2 No Stock (NS)

No Stock is a complementary way of measuring the partners' alignment with the excellence experience Farfetch wants to provide to customers. Once again, both No Stock Net and Gross are measured.

No Stock Net represents the percentage of ordered items canceled due to a lack of stock on the total items sold, in a particular time frame. No Stock Gross adds the *Suggest an Alternative* feature to the calculation - whenever a partner cannot accept an order due to a lack of stock and an 'Item Swap' is not possible, it has the possibility of suggesting an alternative product, that may or not suit the client. If the client accepts the suggestion, the order follows its normal processing path; if not, a No Stock is declared. The *Suggest an Alternative* hypothesis occurs only after all partners' stock has already been assessed.

The following equations display the calculation method of these metrics.

$$NS\ Net = \frac{Nr\ of\ No\ Stock\ Occurrences}{Nr\ of\ Orders\ Sent} \tag{3.3}$$

$$NS\ Gross = \frac{Nr\ of\ No\ Stock\ Occurrences\ +\ Nr\ of\ SaA\ Accepted}{Nr\ of\ Orders\ Sent} \tag{3.4}$$

These metrics have a high negative impact on the customer experience, as a No Stock occurrence often leads to a lost sale.

3.2.3 Perfect Order Fulfillment (POF)

POF considers all product orders that were received by customers, and counts the ones which arrived on time (according to the EDD sent by e-mail at the time of the purchase) and with the right article.

The Supply Chain Council describes POF as 'the percentage of orders delivered to the right place, with the right product, at the right time, in the right condition, in the right package, in the right quantity, with the right documentation, to the right customer, with the correct invoice. Failure to meet any of these conditions results in a less than perfect order'(Dwyer, 2008).

Therefore, this metric's calculation is currently incomplete, as new features and conditions such as the No Stock evaluation should be included.

The current rule behind the POF calculation is the following.

$$POF = \frac{Orders\ which\ arrived\ Just\ In\ Time\ and\ weren't\ returned\ due\ to\ Wrong\ Item}{Total\ Nr\ of\ Delivered\ Orders} \quad (3.5)$$

3.2.4 Order To Delivery (O2D)

O2D, or Lead Time (LT), describes the time elapsed between the order's creation in the online platform and the order's delivery at the client's house. It comprises all the six steps described earlier and gives a particularly accurate insight on the clients' experience with Farfetch in terms of the time the client was kept waiting for the order. O2D formula is presented next.

$$O2D = Order\ Received\ Date\ \text{-}\ Order\ Creation\ Date \quad (3.6)$$

Delivery Outliers are excluded from this calculation. The evaluation whether a product order is to be treated as a Delivery Outlier involves three considerations and is computed as following:

```
case when [GoodDataQuality] = 'Yes'
and [OutlierSOS]= 'No'
and [OutlierTT] = 'No'
then 1 else 0 end as [DeliveryOutlier?]
```

A product order record is considered to be of good quality when the respective tracking information is integrated in Farfetch's system; if there is manually inserted information, data is excluded for not being reliable.

Whether a product order is a SoS or a TT outlier, depends on if the values fall, respectively, outside the range given by the following equations.

$$SoS = \mu \pm 3\sigma \quad (3.7)$$

$$TT = \mu \pm 3\sigma \quad (3.8)$$

A previous data treatment is necessary in order to consider outliers by route and by service (standard or express), rather than globally, as these two features influence the SoS and TT average, as well as their distribution.

3.2.5 Forecast Accuracy (FA)

Farfetch forecasts the sales volume for the next seven weeks, both per partner and for the overall company's sales volume. The weekly FA metric compares the forecasted volume from four weeks earlier with the actual sales volume on a particular week, through measuring the effectuated Mean Absolute Percent Error (MAPE).

FA for week w is calculated as following (for the whole Farfetch volume and per partner, respectively), where i represents the day of the week and p the number of partners considered. The total number of partners is defined by N.

$$FA_w = 1 - (\sum_{i=1}^{7} \frac{|Actual_{w,i} - Forecast_{w-4,i}|}{|Actual_{w,i}|}) * 100; \qquad i = 1, \ldots, 7 \tag{3.9}$$

$$FA_w = 1 - (\sum_{i=1}^{7} \sum_{p=1}^{N} \frac{|Actual_{w,p,i} - Forecast_{w-4,p,i}|}{|Actual_{w,p,i}|}) * 100; \qquad i = 1, \ldots, 7, \quad p = 1, \ldots, N \tag{3.10}$$

3.2.6 Incentives 4.0

To stimulate partners to improve their performance, Farfetch has developed an incentives program on a monthly basis. The incentive's value rests on the partners' performance on SoS and NS metrics. Depending on the partner's aggregate score, Farfetch will either give back or take an additional percentage of the partner's Actual Transaction Value (ATV). The incentives policies are shown in Figure 3.3, where values are intentionally blurred due to confidentiality reasons.

		No Stock Percentage								
	%	Range I	Range J	Range K	Range L	Range M	Range N	Range O	Range P	Range Q
Speed of Sending SLA	Range A	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Range B	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Range C	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Range D	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Range E	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Range F	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Range G	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Range H	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Figure 3.3: Table originating partners' performance incentives

The incentives plan has already had several increments and iterations in the past year, as it has to be aligned with the partners' growth. However, this plan treats every partner as equal and every week of the year as having the same target, which isn't entirely accurate.

3.3 Current Visibility and Control over Supply Chain

There are numerous teams involved in monitoring and measuring specific parts within the order management process, sometimes being the same metric measured by more than one team.

The current weekly Supply Chain KPI reporting service has the aspect shown in Figure 3.4. Besides this executive overview of all measures, a deep-dive per region and per tier is also sent, as well as a list of the most important partners both by sold value and by impact (per metric).

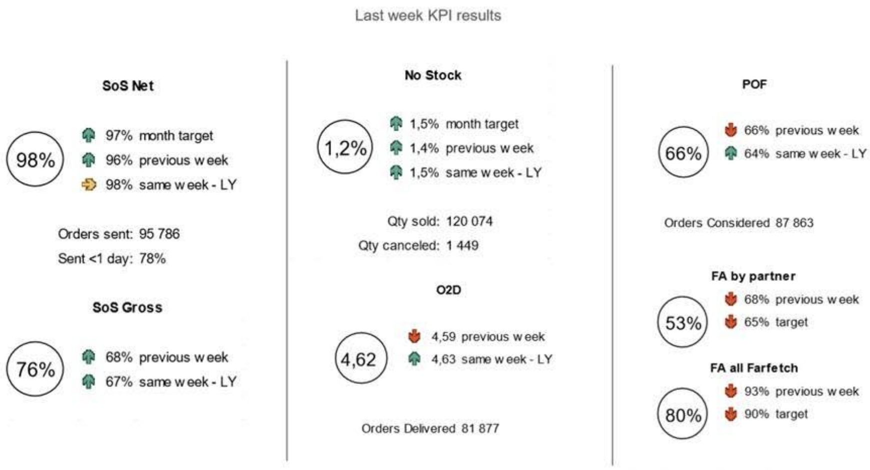
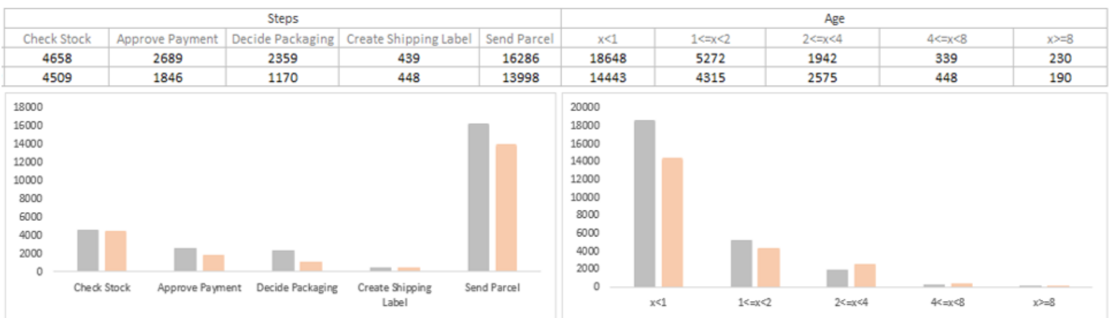


Figure 3.4: View of weekly KPI results sent by the Supply Chain

The metrics' values are provided by Excel Cube, through a very manual, slow and not optimized process. Excel Cube reads the data from Farfetch's database in SQL. Another report, collecting data directly from the database, is sent every day, providing a sight about the present situation of the company's pipeline - it displays the number of orders being currently processed, and enables a subdivision by ongoing step and age of orders. One of these reports is illustrated in Figure 3.5.



Steps					Age				
Check Stock	Approve Payment	Decide Packaging	Create Shipping Label	Send Parcel	x<1	1<=x<2	2<=x<4	4<=x<8	x>=8
4658	2689	2359	439	16286	18648	5272	1942	339	230
4509	1846	1170	448	13998	14443	4315	2575	448	190

Figure 3.5: Daily overview of the pipeline's condition

The last of the Supply Chain's monitoring and controlling routines is the monthly Ops Cockpit. In this presentation, the official monthly values of the KPIs owned by the Supply Chain team are presented to the directors of each department.

3.4 Partner Segmentation

Farfetch has very different types of partners, ranging from small boutiques, which fulfill one order a day, to big warehouses, which frequently exceed DHL's daily picking threshold.

For the latter ones, the current order cycle is not the most efficient and accurate anymore, as they usually push orders directly to step 5 (in the digital system) to reduce time spent in each step, and only then perform the activities that should already have been performed earlier, such as the packaging decision or the shipping documents' printing. Furthermore, such order volumes complicate tasks like the stock check and the package preparation (as orders arrive continuously and not only during a particular period).

There are, essentially, two partner types - boutiques and brands - and both are grouped into four tiers, according to their annual sales volume and annual GMV - if either a particular sales volume or a particular annual GMV is exceeded, partners rise to the next tier. Boutiques are categorized into T0 - Key, T1 - Important, Tx - Standard and SMB - Small and Medium Businesses and, similarly, brands are categorized into B0 - Key, B1 - Important, Bx - Standard and SMB - Small and Medium Businesses. Farfetch offers different conduct and has different annual targets for each tier, and partners can also be moved manually from one tier to another, depending on their strategical relevance. All tiers are updated every six months.

In terms of geographic segmentation, the official subdivision is by the office serving a particular set of partners. Farfetch has offices in Europe (EU), Asia-Pacific (APAC), the United States (US), Japan (JP) and China Region (CR), which deal with a particular set of partners, and each office corresponds almost entirely to the geographic region. Once again, annual targets are defined for each office's partners.

Regarding customers, these are classified into five categories, according to their expenses. If an annual amount in sales is reached, the customer steps to the next category. As this classification is currently being reevaluated and systematized, it will not be considered in the current project, as it will be explained later.

3.5 Seasonality

There is a weekly seasonality in sales due to, essentially, holidays or special commercial promotions. The launch of new collections also contribute significantly. Figure 3.6. illustrates the number of orders placed in 2018, by week.

Within a week, the order creation's weekday also plays an important role in Farfetch's operations, which are running 24h, as Farfetch has partners in the whole world. As partners do not fulfill orders on weekends, this factor influences metrics such as O2D.

Furthermore, Farfetch's customers are also spread around the whole world, which means that orders are placed continuously. The metric After Hours Orders, defined in Chapter 4, gives insight on the hourly distribution of order placement.

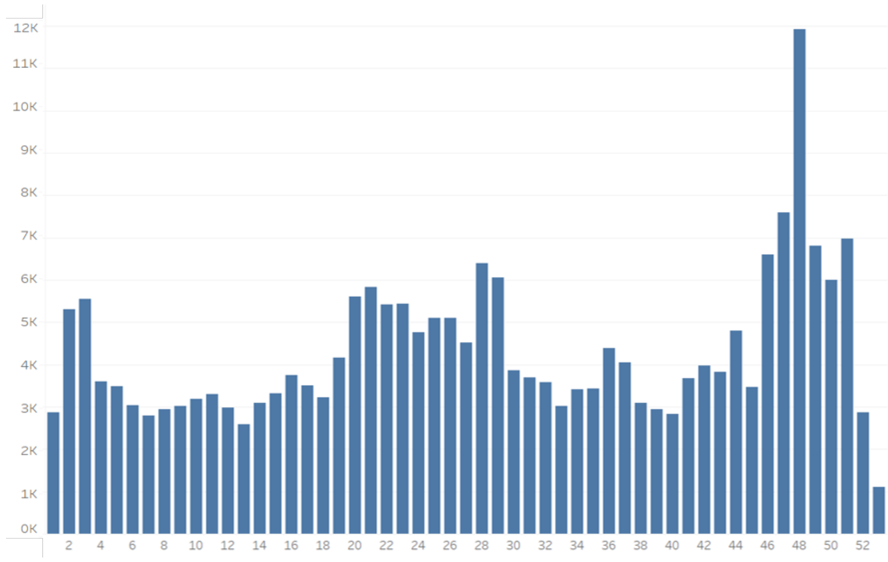


Figure 3.6: Number of orders placed per week in 2018

3.6 Fulfillment by Farfetch - FxFF

This recently created business unit is, essentially, an additional service created by Farfetch, in which the company acts as a sort of a 3PL, expanding its services to warehousing and stock management. Transportation is, however, not ensured by Farfetch, being still certified by an 'absolute' 3PL.

The stock Farfetch deals with may be divided into three categories, according to the entity managing it. 1P is inventory owned by Farfetch (Browns and Stadium Goods stock) and stored in one of Farfetch's warehouses in the US, APAC or EU. 2P is inventory Farfetch manages, although it doesn't own it - it is stock the partners have requested to place under Farfetch's control in one of the company's warehouses. 3P is stock owned and managed by the partners and will be called Business as Usual (BaU) during this project. The partners are responsible for their operations.

FxFF, therefore, encompasses both 1P and 2P and designates all the orders of products under Farfetch's control, whose order processing is almost entirely fulfilled by the company.

3.7 Improvement Opportunity

Excel Cube, collecting data from the SQL database, is used as all necessary filters to be applied to metrics are already defined there. However, this solution's performance is very low, due to the enormous number of measures and filters, which turns the weekly monitoring into a difficult task.

The company's gradual move into a customer-centric mindset requires the definition and monitoring of new, complementary KPIs, which reflect the company's mentality.

To aggregate both already existent and new KPIs in a single, robust and automatic dataset, feeding a thorough dashboard, which evaluates the end-to-end supply chain from a customer perspective, would on the one hand ease and quicken the team's monitoring routines and on the other solve the leading problem of scattered data.

Every useful filtering option should be included in the dashboard, in order to reduce the number of static elements in reports: depending on necessity, users would be able to consult the needed data through combining multiple filters.

From the moment where the process is perfectly visible, it should be possible not only to identify pain points in the process, but also to define actions to tackle these problems.

Therefore, there is the urge to assembly all relevant KPIs in one common, robust, automatic, customer-oriented and easily usable dashboard, which acts as a control tower for the health of the entire supply chain system. When consulting the dashboard, users should be able to identify pain points in the process and define actions to tackle these problems.

As a way to achieve the referred desired result, a central SQL table, where every important information is stored, must be created. This table should be easily upgraded, and reunite every possible important metric.

Chapter 4

Procedure

This chapter will cover the methodology followed over the project, from the problem identification to the model's projection and development.

The projects' phases were inspired by the steps suggested by Vilarinho et al. (2018), as showed in Figure 4.1.

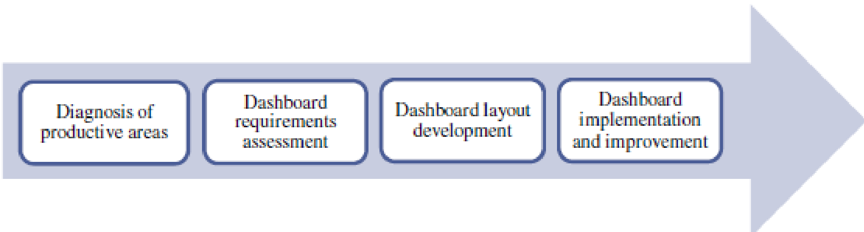


Figure 4.1: Followed Dashboard Development Procedure

Initially, the whole ordering process was analyzed and the company's business scope carefully examined. The main processes were mapped, intending to identify every system's feature or detail that has an impact on customer's experience. Afterwards, a set of effective and significant KPIs to measure the system's end-to-end performance have been defined, having the dashboard requirements in mind, as well as both the SMART and the customer-centricity criteria. Already existent, but important, KPIs were maintained, and the methodology to define new KPIs was inspired by the in chapter 2 referred EAM approach (Kaganski et al., 2017). Several stakeholders from teams Supply Chain, Partner Success, Fulfillment Operations and Delivery were questioned about which information would be useful to them, respecting the company's strategy. A technical file of each selected KPI was developed based on the KPIs' features presented earlier by Domínguez et al. (2019), with the goal of clarifying their meaning and calculation method to the whole company. These are presented in Appendix B. The several features, which act as filters, are also presented and are of particular significance, as the filter mix is what permits deep dives and the identification of unusual or unwanted values.

Afterwards, Farfetch's database was thoroughly investigated, in order to collect all necessary information to calculate the defined metrics directly from its source. This involved several iterations, as the final dashboards' requirements were not clear from the beginning and the users' demands faced some adjustments. A dataset storing all relevant data was constructed.

Finally, the dashboard views were designed, set up and iterated until all the users' requirements were met and visualization principles were satisfied.

This project does not aim at measuring or monitoring Customer Satisfaction *per se* - there are special metrics being monitored with that intent (for example NPS - Net Promoter Score) and they are not owned by the Supply Chain team. Customer centric metrics, in this scope, refer to metrics which provide any kind of feedback on Farfetch's operations' real impact on customers.

As several authors have indicated, the constant focus on the dashboard's final result is a crucial concern during its elaboration. Thus, the main goal of obtaining a customer centric view of the supply chain process is to be considered at all times.

4.1 Requirements Assessment

According to the definitions provided by Vilarinho et al. (2018), the dashboards coming up from this project will combine two purposes: the monitoring of critical activities and processes and the analysis of the roots of problems, by enabling multiple filtering options and deep dives.

The dashboard is to be built resorting to visualization software Tableau, as this is the software used by the whole company for monitoring and reporting issues.

Tableau is capable of receiving inputs in various formats, such as tables stored in SQL or Excel files. However, the robustness of inputs has to be cautiously analyzed and is a crucial point for the accuracy and usability of the tool.

4.1.1 Farfetch's Database

All data Farfetch collects is stored in SQL, in two distinct databases: one containing almost live data and one which is refreshed once a day. The second database is fed by the the first database - therefore, every (past) information should be found in both databases. However, reality is different and useful tables and analysis created by some teams can sometimes be found only on one of the databases. The process of identifying where to find a particular information is especially laborious and cumbersome. Therefore, the perspective of having one main central table containing all important data in a structured way is especially appealing.

Inside each database, a table is identified by a folder, a schema and a name, as follows: *Folder.Schema.Name*.

The tables created for this project were stored in folder *BI_ANALYTICS* in the once a day refreshed database, and incorporate the abbreviation 'SCA' in the table's name, so that it is easier to locate them in the high number of existing tables.

4.1.2 Definition of new metrics

To get insight on relevant business elements that were not yet being collected, monitored and analyzed by Farfetch, there was the need to define new metrics.

As a result of meetings with multiple teams, the following new metrics have been developed during this project:

- Perfect Order Fulfillment (reevaluation);
- Number of Ruined Days;
- After Hours Orders;
- Live evaluation of pipeline status.

In addition to these metrics, a comparative analysis of BaU and FxFF business types has been performed, as well as an analysis of all metrics only for customers buying in Farfetch for the first time.

The live evaluation of the pipeline status was redesigned, although the same data obtainment method has been used.

4.1.2.1 Perfect Order Fulfillment

As explained in Chapter 3, the company's current definition of a perfect order is deficient: it is based only on delivered orders, ignoring orders that have never been delivered due to a lack of stock or a lost parcel. Additionally, the current metric is calculated on an item order basis, which is not the most accurate measure of the customers' overall experience and satisfaction. Customers' satisfaction is best evaluated by the performance of the whole portal order or, at least, boutique order.

Thus, the new POF calculation covers no stock situations, returns due to wrong items and delivery accuracy (in terms of time), and is calculated on a portal order granularity, instead of a product one. A portal/ boutique order has only two possible POF values - 100% or 0% - respectively, whether all included products were delivered in perfect conditions or not. The new formula is presented next.

$$POF = \frac{Nr\ of\ Boutique\ Orders\ that\ fulfilled\ all\ 3\ criteria}{Total\ Nr\ of\ Sent\ or\ 'Cancelled\ due\ to\ No\ Stock'\ Orders} \tag{4.1}$$

A comparison of the POF before and after the reevaluation is presented in Figure 4.2, for the year of 2018. As expected, the KPI's weekly value decreased.

The waterfall chart presented in Figure 4.3 illustrates the effect of all the criteria on the POF value - No Stock, Too Early, Too Late and Return due to Wrong Item.

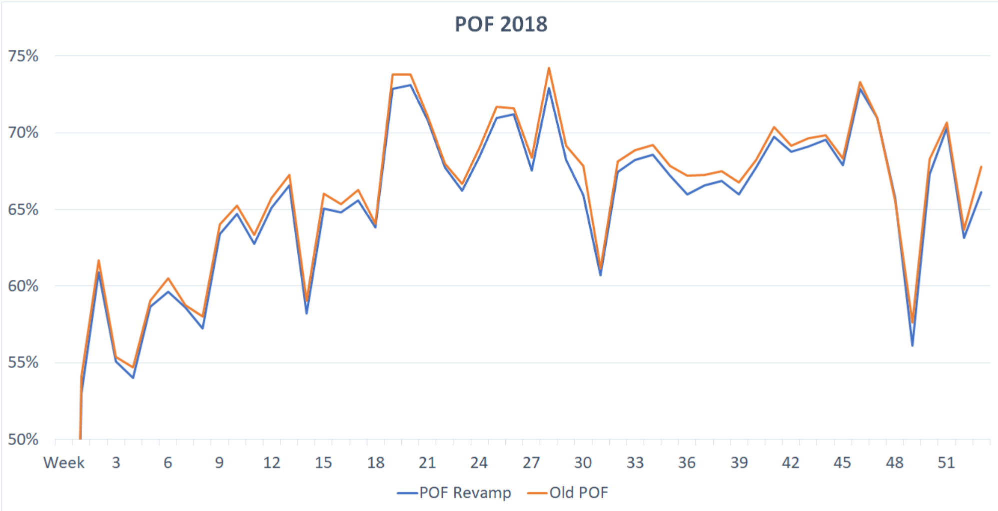


Figure 4.2: POF values in 2018, before and after the revamp

The company has defined that an order that arrives at the client's house too early is not perfect, which is, precisely, the most impacting criterion. However, partners' performance shall not be affected - in fact, an early delivery means that the partner performed very well; Farfetch should just have predicted delivery times better. Therefore, a secondary metric called *POF_Partners* is also to be defined, which considers early deliveries as perfect orders.

The presented values refer to an evaluation to a boutique order granularity. As it will be explained later, the developed query also enables a grouping by portal order, which is the best proxy to a value for customer satisfaction. However, the team opted to monitor POF at the level of boutique orders, so that partners' performance can also be brought to light by the metric.

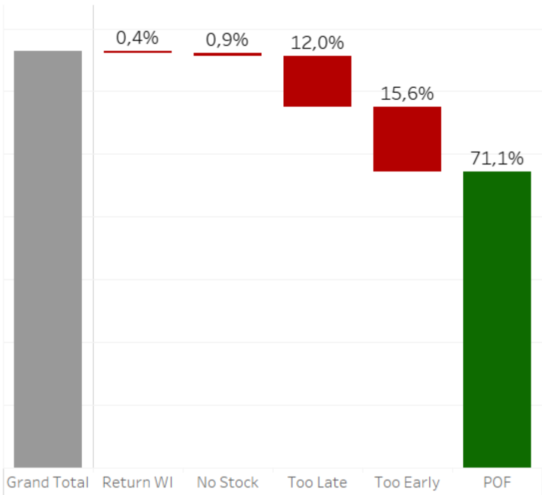


Figure 4.3: Relative relevance of criteria affecting POF

4.1.2.2 Number of Ruined Days

A new metric, used by other e-commerce companies such as Amazon, is to be implemented, as the company has already expressed the need for it in past months. It is called 'Number of Ruined Days' and sums all the days Farfetch ruined by not meeting customers' expectations, in a particular time frame (relatable to 'Things Gone Wrong').

This metric is to be presented as an absolute number, to shock and raise awareness of the actual consequences of Farfetch's incapacity to meet the clients' expectations, and in the form of average days ruined per ruined order, in order to facilitate the dashboard users' perception of the harm caused.

Matching the Perfect Order Fulfillment metric, the Number of Ruined Days is calculated from a client's perspective. It refers to the total amount of days a *boutique* order ruins, being also possible to be calculated in terms of ruined portal orders, if preferred.

The criteria for considering a day as having been ruined by Farfetch are the occurrence of a no stock, a failure to meet the EDD and a return due to a wrong item. There are, in fact, more aspects that can ruin a client's day and that should be included, such as an imperfect CS contact. However, for the sake of consistency, the criteria for this metric are the same as the ones for classifying an order as perfect.

Concerning the failure to meet the EDD, both early and late deliveries are considered to be non-perfect experiences for the customer. However, whereas an order is considered to ruin all the backlog days if it is delivered too late, it is seen as ruining 'just' the delivery day if it is delivered too early. No stock occurrences and returns due to the shipment of a wrong item ruin one day, namely that occurrence's day.

Historically, of the orders that were not perfect, approximately 80% ruined one day, 10% ruined two days, 5% ruined three days and the remaining 5% ruined more than 3 days. To this group belong all outliers, late cancellations, fraud issues and lost parcels.

4.1.2.3 After Hours Orders

After Hours Orders are orders that were placed outside the partners' working hours. These orders are expected to have higher SoS and, consequently, O2D values, as they were inevitably stuck in Step 1 at least until the partner's next day opening. In this way, considerations regarding the partners' time zones have to be included in the calculations.

This metric is particularly relevant for network design, guaranteeing that warehouses are located in the most favorable time zones, and enabling the choice of their labor hours advantageously. Furthermore, pickup times at the partners can be scheduled to the most suitable hours.

As there is no data on the partners' working hours, several assumptions were made:

- all partners work only on weekdays;
- all partners' working hours are from 9h to 18h;

- daylight saving times were excluded from the calculation.

Figure 4.4 depicts the number of placed orders by the local hour of the partner fulfilling the order, as well as the metric's value.

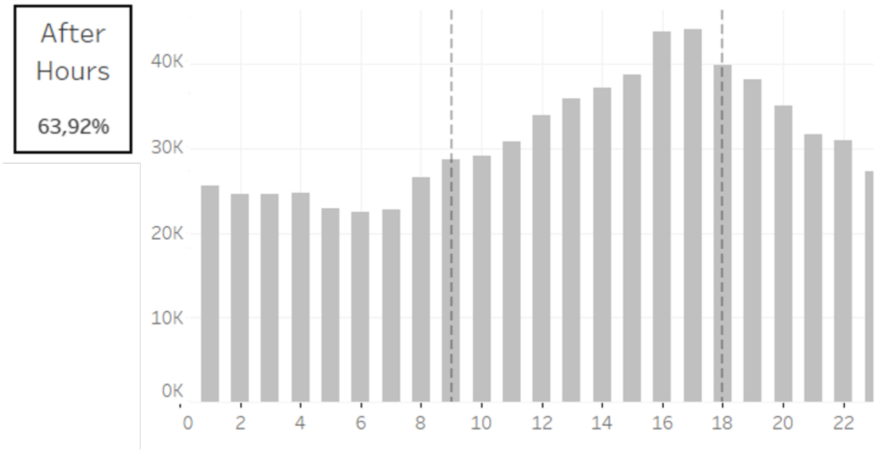


Figure 4.4: Hourly Distribution of Order Placement

4.1.3 Automation

The dashboard views have to be constantly updated. Therefore, both the feeding SQL queries and Tableau itself have to be refreshed with a certain frequency. Automatic refreshment leads to time savings and consistency.

A script to automatically run the necessary SQL queries has been developed. The run of a job on stored procedures instead of on simple queries permits that the owner alters the tables assuring that the job works nonetheless (as long as the procedures' names remain the same). This is particularly useful, as the input tables are not yet finalized and are always susceptible to alterations. So, one procedure to call each input table has been created, and were then designated to be executed automatically by a job, with a specified frequency. The job was scheduled to run every night, so that the displayed values are always as accurate as possible. If needed, a manual update is also possible at any time. A general procedure's script is presented in the end of Appendix C.

Tableau also enables automatic, scheduled data refreshment with a specified frequency. Reasonably, the Tableau refreshment has to be performed after the input tables are refreshed, and is also done every night.

4.2 Tool Development and its Organization

The next sections illustrate the whole process of the tool's development, considering the dashboard views' requirements.

SQL was the main software during the development of this project, as data was collected and organized there. However, particularly challenging tasks have been performed with the use of Python - this coding language was selected due to the availability of powerful libraries and to the vast community of Python developers in the Internet who are willing to help new joiners in various stages of their development.

4.2.1 Goals

Due to technical limitations, as it will be explained in the next sections, it is necessary to create multiple dashboard views in Tableau - the users can then select and consult the view that is most suitable for their needs. A weekly and a monthly view of each metric will be presented, as teams differ on the frequency they use and report specific metrics. Since the Initial Public Offering (IPO), in October 2018, there is also the need to report quarterly results, wherefore a quarterly view shall also be developed.

Additionally, a live insight on the pipeline's condition will be provided, as well as a graphical overview of some KPIs trends over the last year and a synthetic, weekly overview of the performance of the top 20 partners by sold value ($). A weekly analysis of the top 10 partners by weight (per KPI) is also considered in the same view.

Lastly, and due to the Supply Chain team's demands, a deep dive view on the O2D metric is also to be developed.

In order to boost the Supply Chain's monthly presentation in the previously referred monthly cockpit, a synthetic view of each KPI (O2D, POF, RD, NS, SoS<1d, SoS<2d, FA) is to be presented in a dedicated, individual sheet. The form of these views is to be intuitive and uniform.

4.2.2 Selected KPIs and Their Measurement

As presented earlier, the Supply Chain team is the owner of NS, SoS, FA, O2D and POF metrics, wherefore these are necessary to be included in any report.

The customer centricity requirement is achieved through metrics like O2D, POF and NrRD, which best describe customers' experience and satisfaction.

In addition to the weekly and monthly value, the past progress of some KPIs gives meaningful insight on the supply chain's progress, and shall, therefore, be incorporated.

Regarding the live pipeline status, the number of orders currently being processed and their age provide an overview on how the system is performing. Both these metrics' expected value ranges vary with the time of the day and the day of the week.

4.2.3 Metrics' Calculation

The final dashboards are to be sustained by multiple datasets, constructed especially for the purpose of this project.

A general methodology used while selecting and manipulating data from the databases is the organization of data in binary columns, put up by means of conditional clauses (Patil et al., 2017). This procedure will simplify the following calculation and visualization of the KPIs in Tableau, especially in the case of aggregated KPIs. The metrics are subsequently calculated in a very intuitive way, using the following generic formula:

$$Metric\ x = \frac{Sum\ of\ x}{Count\ of\ x} \tag{4.2}$$

The decision to group all the relevant information in a single table and to calculate the metrics only in Tableau enhances the flexibility of the tool, as it allows the display of aggregated and disaggregated data.

The main difficulty during the dashboard's design phase was the fact that each metric has a different time basis: NS is calculated based on the no stock evaluation date, SoS based on the order send date and 02D based on the delivery date. As the dashboard's goal is to present a weekly view of what exactly happened on that particular time span, Tableau is supposed to calculate each metric based on the appropriate calculation rule, but showing the values of each metric for the week or month chosen by the user.

Therefore, four parameters - Year, Quarter, Month and Week - and calculated fields for each KPI were created. In the weekly view, when the user selects the desired year and week, for example, Tableau compares the appropriate date to calculate a singular KPI with the parameter and shows the value for the desired year and week. Examples of created calculated fields are presented in Appendix D. Each metric to be measured has to be defined and calculated using this methodology. This is the only way to aggregate KPIs which use different time basis under a single filter (the parameters determine what is showed), commanding them all.

This explains the discrimination between a monthly and weekly view. A calculated field can either show a weekly or a monthly value, so to present both the weekly and monthly value for a particular metric, two distinct calculated fields have to be created.

It would be possible to aggregate everything in a single dashboard view, but as the parameter 'Week' would only command certain KPIs and the parameter 'Month' the others, this approach would result in an overly complex and inefficient, as well as disorganized, solution.

The several stakeholders and future users of the dashboards accepted the idea of having two distinct visualization options. This method even permits a better split of information, avoiding misunderstandings.

4.2.4 Development of the input tables

The following sections describe the study behind the design of each dataset, as well as the process of coding them in Structured Query Language (SQL). In some specific applications, SQL code was directly written in Tableau.

The codes originating the constructed tables are presented in Appendix C.

The choice of having an SQL dataset as an input to the model instead of a Cube, which is able to return information more quickly, is justified because some Tableau features are not available to Cube data sources, wherefore it is worthy to connect Tableau directly to the relational database. Cube data sources also are not as flexible and scalable as relational data sources, and if requirements would change after the Cube had been built, this method could lead to a dead end.

4.2.4.1 BI_ANALYTICS.dbo.SCA_Scorecard

Following McNeeney (2005)'s suggestion, and due to Farfetch's database untidiness, a single table collecting all relevant data for calculating the KPIs was built, to assemble all necessary data in a single location, constructed in a way that it was easily updated and new information added.

The necessary data is scattered over multiple sources, both in structured and unstructured forms and, therefore, the first step was to assess which information is actually needed. Even this circumstance is susceptible and probable of being adjusted and iterated, as during the modelling process it is possible to come to the conclusion that more data is needed. Thus, the dataset's disposition was carefully forethought and developed.

The Supply Chain team needs to have the most granular visibility on the entire process. Therefore, each product order has to be identified, being the later grouping by boutique or portal order possible, if needed. Having this in mind, the unique key of the table's rows shall be the product order's identifier - the *Orderline*. Generally, the needed data regarding each product order consists, essentially, of all information on its identification, on its origin and destination and on all the time stamps during the order processing. This is the primary data, which is collected directly from Farfetch's databases. Secondary data, defined as information that was calculated based on other tables' information, is also grouped and organized in this table - mainly through binary columns.

In order to be upgrade-friendly the table is based on several provisional sub-tables. This methodology is also preferential when considering the system's performance: the amount of data is huge and it is collected from multiple locations, involving several joins in SQL, which make the query very heavy.

The table *SCA_Scorecard* is, thus, composed by five sub tables. *Overview* presents all information regarding the product order's identification, *AddInfoStore* contains all relevant data regarding the partners' characteristics, *KPIs* essentially displays whether a product order is to be considered in a particular KPI's calculation or not, *AllDates* provides all relevant time stamps during the product order's processing and *Returns* includes everything related to the eventual return process of a product order. Due to this topic's complexity, data referring to whether a product was returned or not is stored in a separate subtable. Each subtable has one column in common - *OrderLine* - which makes it possible to, ultimately, join them into the final table, as showed in Figure 4.5.

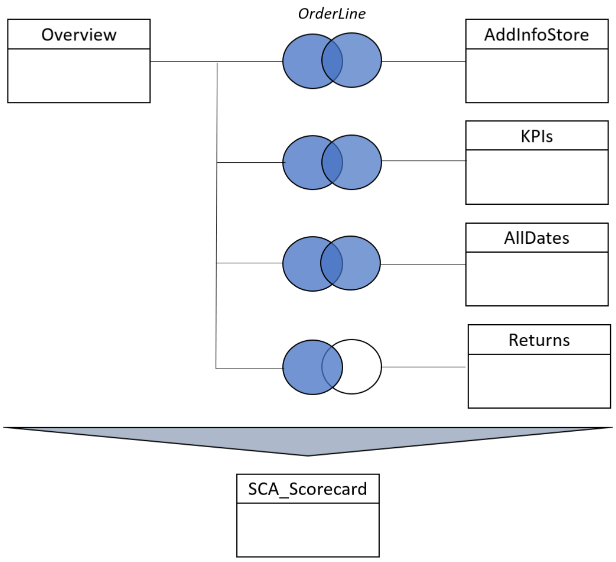


Figure 4.5: Constitution of the main table feeding the visualization tool

As only about 20% of all product orders are submitted to the return process, subtable *Returns* is connected to subtable *Overview* by a left join. Every other connection is established using an inner join.

Only data referring to product orders placed in 2018 and 2019 was considered. Due to the company's changes verified in the last two years, earlier data wouldn't be relevant for the current project.

By default, SQL considers that weeks start on Sunday and end on Saturday. However, internally, weekly metrics refer to the time starting on Monday and ending on Sunday and, for consistency, this shall be maintained. Therefore, it is necessary to command this rule to SQL in the beginning of each query, so that the software can calculate the orders' week time stamps based on it (see Appendix C).

Some columns have not been used specifically for this dashboard, but the point of constructing this table was also to develop a robust database, available to everyone and able to fulfill their data needs. Some columns were built to already prepare further analyses.

Returns are the subject of another ongoing project within the Supply Chain team, wherefore the information included in this table is merely a first step of a broader study to be performed in the near future.

4.2.4.2 BI_ANLYTICS.dbo.SCA_POF

This KPI's requirement of being calculated per product order but then analyzed per portal order under certain conditions, makes it necessary to compute the POF calculation in an additional and independent query, originating the *SCA_POF* table.

Columns *Year_POF*, *Quarter_POF*, *Month_POF* and *Week_POF* give insight on the boutique orders' POF evaluation time stamps. In this case, both (eventual) cancellation due to No Stock date and Received Date of all product orders within a boutique order have been analyzed and the latest one selected as the 'POF date'. Each boutique order is supposed to contribute to only one week's or month's metric.

POF is calculated considering the date the boutique order is received by the client. However, product orders that had a No Stock occurrence have never been received, which explains why they have to be analyzed according to their No Stock Evaluation Date. Furthermore, if a portal order includes more than one boutique order - which will, most likely, be delivered at different times - the week or month to consider for POF calculation is the latest of the boutique orders delivery date.

4.2.4.3 BI_ANLYTICS.dbo.SCA_NrRD

Like POF, as the fundamental basis for the calculation of the number of ruined days is the boutique order, a third table was built, in order to store all data referring to the metric Number of Ruined Days.

The methodology used to build this table was the same as for the POF. This separation of tables enables future improvements of the metric.

Whereas in table *dbo.Scorecard* no KPI is calculated, both metrics POF and NrRD are calculated in their respective SQL tables.

4.2.4.4 BI_ANLYTICS.dbo.SCA_FA

Forecast accuracy, as explained in Chapter 3, was already measured by the Supply Chain team. It has a particular calculation method, as it compares the forecasted and the actual sales volume, in a particular week.

There is a table in the database containing all the forecasts from previous weeks and the forecast accuracy is calculated directly in Tableau, establishing two connections between two queries and the SQL table. This is the final dashboard's fourth source.

A minimal change was performed on the SQL table, in order to visualize data as desired.

4.2.4.5 Joins in Tableau

The presentation of the current pipeline situation uses live data, which is collected from the (almost) live database. In this case, the goal consists on having visibility on what is happening right now, to detect any existent problem and to act proactively in accordance. As the query delivering this kind of information is not heavy, the calculation is performed directly in Tableau. The already existing query was used.

4.2.4.6 BI_ANALYTICS.dbo.SCA_Timezones

This table is not an input table of the visualization tool; instead it is used for the construction of *SCA_Scorecard*, namely in the attainment of several columns of subtable *AddInfoStore* (see Appendix C).

The partners' coordinates and their time zones and offsets towards UTC (which were not listed in the company's database) were obtained from API Mapbox, using Python for the computation (code shown in Appendix E). The results were imported into Farfetch's database as a table, which was joined with others to build *SCA_Scorecard*. Lastly, the metric was calculated in Tableau. The following table exemplifies the generic format of the created table *SCA_Timezones*.

Table 4.1: Preview of *SCA_Timezones*

LocalID	CityCoords	TMZ	Offset	DST_Offset
10011	[51.5072, -0.1275]	Europe/London	0	1
15310	[33.9864, -117.5227]	America/Los Angeles	-8	-7

The described procedure has to be carried out after the on-boarding of new partners, so that the table is always updated.

4.2.5 Dashboard views construction

The dashboard views were designed having in mind the best practices and advice found in the literature and referred in Chapter 2.

The dashboards provide all the relevant information in about 5 seconds, which is sustained by the inverted pyramid principle: to display the most significant insights at the top of the dashboard, trends in the middle and details at the bottom (Hertz, 2018). This general guideline was used to build all the views, and adapted to each view's peculiarities.

In order to be interactive, flexible and functional, the developed dashboards include filters and hierarchies, conditional formatting, drill-down features and the possibility to online publishing so that the information is available to everyone who needs it. Automatic data refreshment with daily frequency is also provided.

Not all information shall be presented in a single view, in order to not overwhelm users with too complicated visualizations. Along with this principle, the referred software limitations, which required to build multiple dashboard views, ultimately ease usability.

The perception theory and common dashboard practices suggest that only a few colors must be used (Kwapien, 2016). In order to align the dashboards with the company's branding, dark red was used in the dashboards' titles and defined as the dashboards' main color.

To signal the KPI's status options, the colors red and green were chosen, with the red color being darker than usual, to match the titles' color. Grey was used to depict each graph, as it is a neutral color. Graphs encompassing color ranges exhibit an orange palette, varying the saturation for straightforward readability. In the case of the POF waterfall chart, contrasting colors were used, to help the user to quickly differentiate the data (Shander, 2017).

Annual targets were depicted as light grey dotted lines in all graphs, so that these are perceived as reference lines and not dimming the graph's main information.

In order to enhance the understandability of tabular contents and to avoid misunderstandings, alternate white and grey rows were used.

4.2.6 Pipeline status benchmarks

During this project, an initial solution for a benchmark for the live pipeline status was proposed. This solution involves the pipeline's comparison with the past week's minimum, average and maximum number of orders for each step, obtaining a historical range, which serves as a reference for this week's pipeline. However, this is a considerable simplification as this model only considers absolute values and treats each week as equal, ignoring the presence of holidays or promotions, which heavily impact the number of orders.

The code used to get the referred reference band is presented in Appendix F. The output is a table with the format shown in Table 4.2, which can easily be converted into a stacked bar chart.

Table 4.2: One week's obtained reference values per step (fictional values used)

	Step 1	**Step 2**	**Step 3**	**Step 4**	**Step 5**
Min	11 846	1 032	8 935	390	7 028
Avg	19 867	2 637	11 837	561	16 130
Max	35 247	4 292	16 878	1 255	43 474

Unfortunately, the obtained reference band could not be integrated with Tableau, due to the way the live pipeline status is currently calculated. However, this table, or chart, can be presented along with the pipeline status' dashboard, and consulted, if necessary. Ideas for the further development of the pipeline's benchmarks are enumerated in Chapter 6, as next steps.

Chapter 5

Final Results

In this chapter a brief explanation of the dashboard views' development and functionality is provided. A print screen of all dashboards developed during this project are presented in G.

In the weekly, monthly and quarterly views, the graphs' axis were deleted so that the company's internal targets for the respective metrics cannot be identified. The same was performed on the monthly Ops Cockpit views.

5.1 Weekly KPIs

The main dashboard view, providing a weekly sight of the most important KPIs evaluating the end-to-end supply chain process, is presented in Figure 5.1, using fictional values for the metrics.

The KPIs' values are presented at the top of the dashboard, as well as their status towards the overall annual target - red if under the target, green if above. Some metrics do not have targets, and are shown in black. The displayed metrics are grouped into five logical columns.

The O2D metric is divided by steps and presented as a stacked bar. This view allows the user to see the average time spent in each step, as well as before, in and after Customs. The vertical dotted lines represent days, to help the users' interpretation of the displayed information.

Next, the user is confronted with two graphs - the one on the left shows the split of O2D by steps for the top 10 destination countries by number of orders (the countries' names were blurred for confidentiality reasons). The waterfall chart on the right is a particularly powerful tool to deepen POF, and provides a clear visualization of the relative importance of the factors contributing to an order not being perfect.

The evolution of the four main KPIs owned by the Supply Chain team - NS, SoS, O2D and POF - is showed at the bottom of Figure 5.1. The displayed values correspond to the current week and the line shows the metrics' trend in the past three weeks.

Figure 5.1: Dashboard view providing a weekly insight on the whole end-to-end process

On the right side of the dashboard, the user can define the parameters - Year and Week - commanding the dashboard information. The user can only select one week at a time, and if the current week of the current year is selected, week to date values are presented.

Underneath the parameter, a concise table of the number of orders considered in the specified week is provided, allowing the user to convert percentages to absolute numbers, if needed. The percentage of returns during the specified week is also presented, as a mere informative value. As stated before, the returns process was not object of research during this project.

All possible filters are listed below the referred table, as drop down values. They apply to all KPIs and can be combined at the users' will. An 'Apply' button enables that the computation is only performed after the user has selected all desired values. A detailed view of the filtering features is presented in Appendix G.

5.2 Monthly and Quarterly KPIs

Two further dashboard views were developed, which look exactly like the weekly one, except that KPIs are measured on a monthly and quarterly basis, respectively. The only KPI that is not included in these views is Forecast Accuracy, as the weekly accuracy is the only value that is important to measure. Figure 5.2 presents the monthly dashboard view.

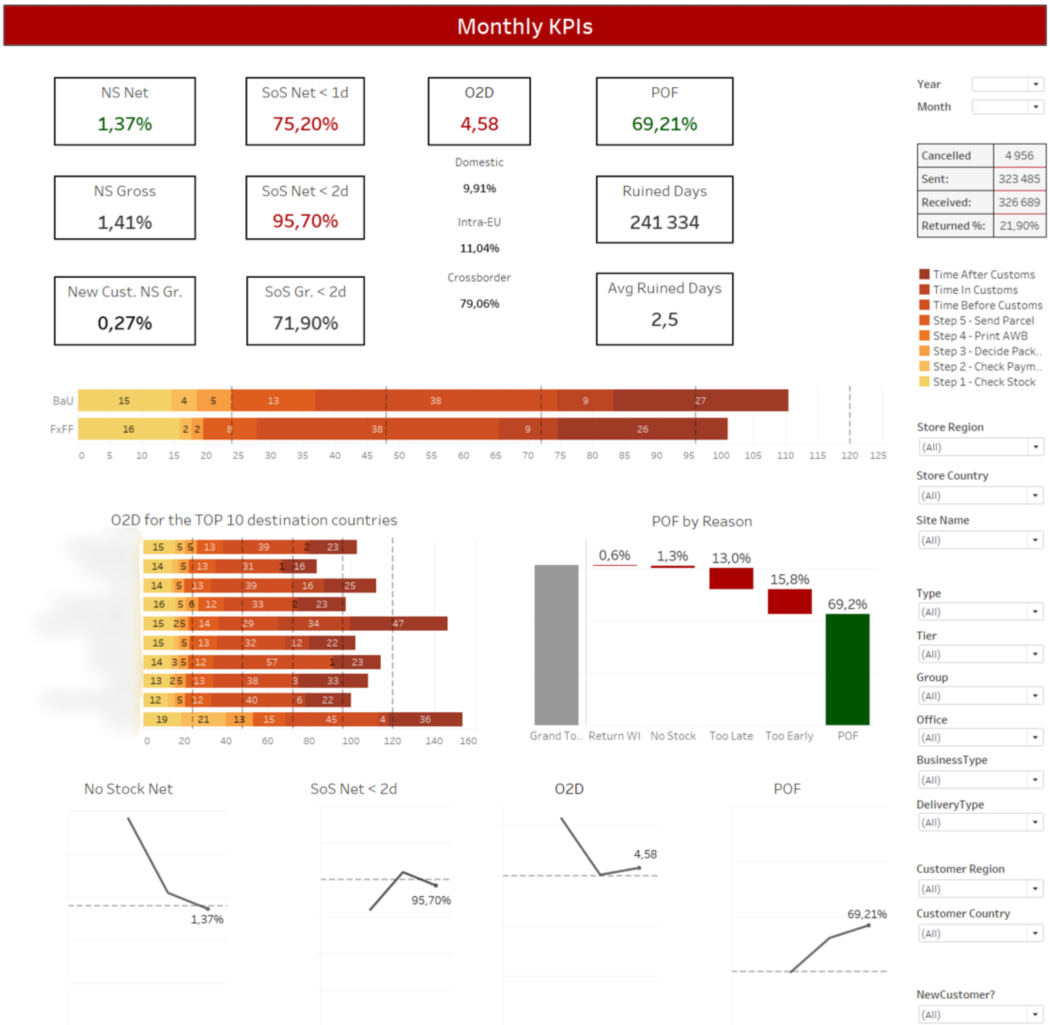


Figure 5.2: Dashboard view providing a monthly insight on the whole end-to-end process

The graphs showing KPIs' past trends have one limitation: only one year's values can be showed at the time, due to the parameter specification. Thus, in the case of the quarterly view, the referred graphs are slightly different, so that more values can be showed at the same time and a trend identified. As the quarterly dashboard view is identical to the weekly and monthly ones, Figure 5.3 shows solely the referred graphs depicting the metrics' past performance.

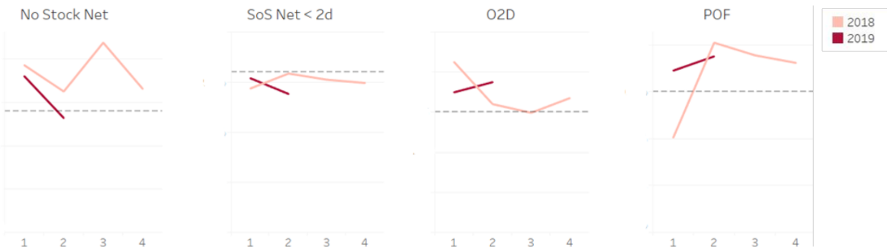
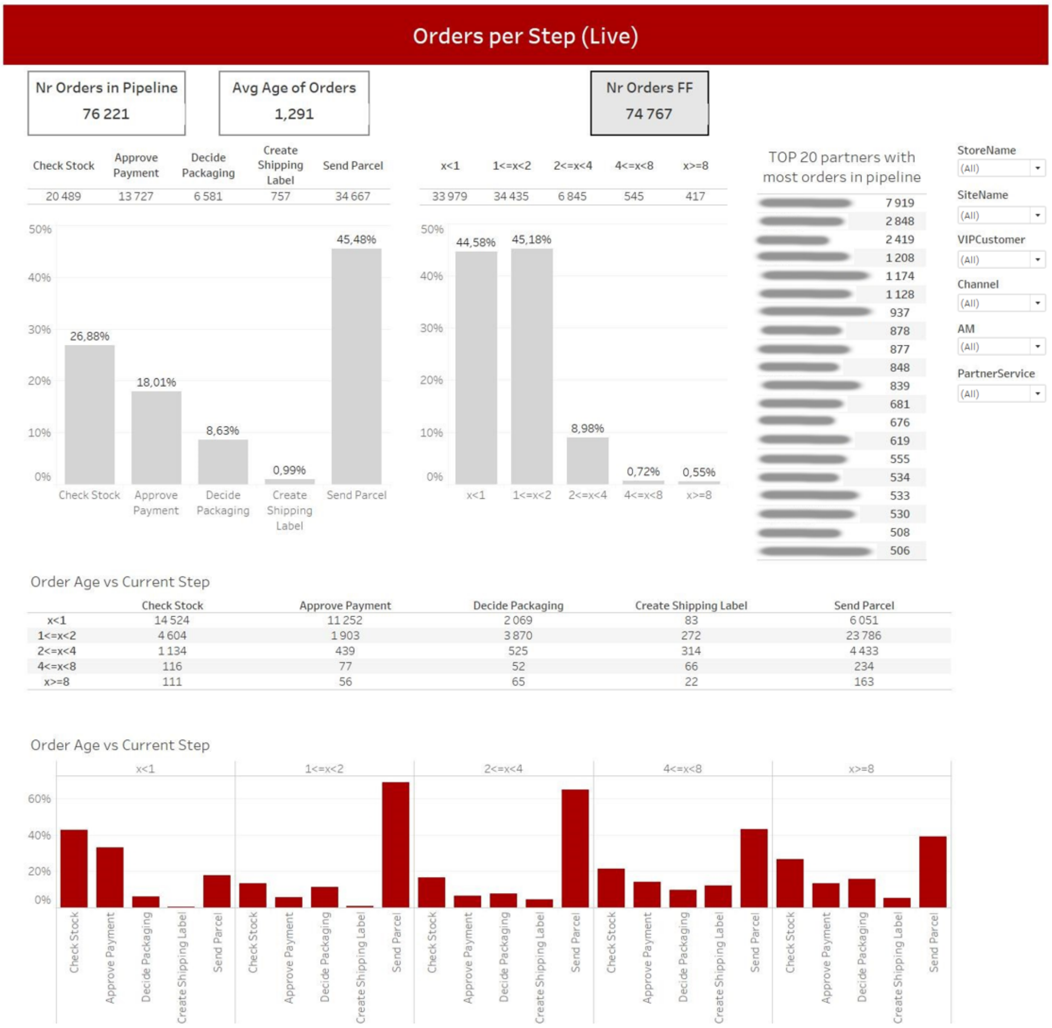


Figure 5.3: Detail of the quarterly dashboard view

5.3 Live: Orders per Step

Figure 5.4 presents the developed dashboard view of the live pipeline status, allowing a live insight on the number of orders being processed per step, and the age of all orders.



	Check Stock	Approve Payment	Decide Packaging	Create Shipping Label	Send Parcel
x<1	14 524	11 252	2 069	83	6 051
1<=x<2	4 604	1 903	3 870	272	23 786
2<=x<4	1 134	439	525	314	4 433
4<=x<8	116	77	52	66	234
x>=8	111	56	65	22	163

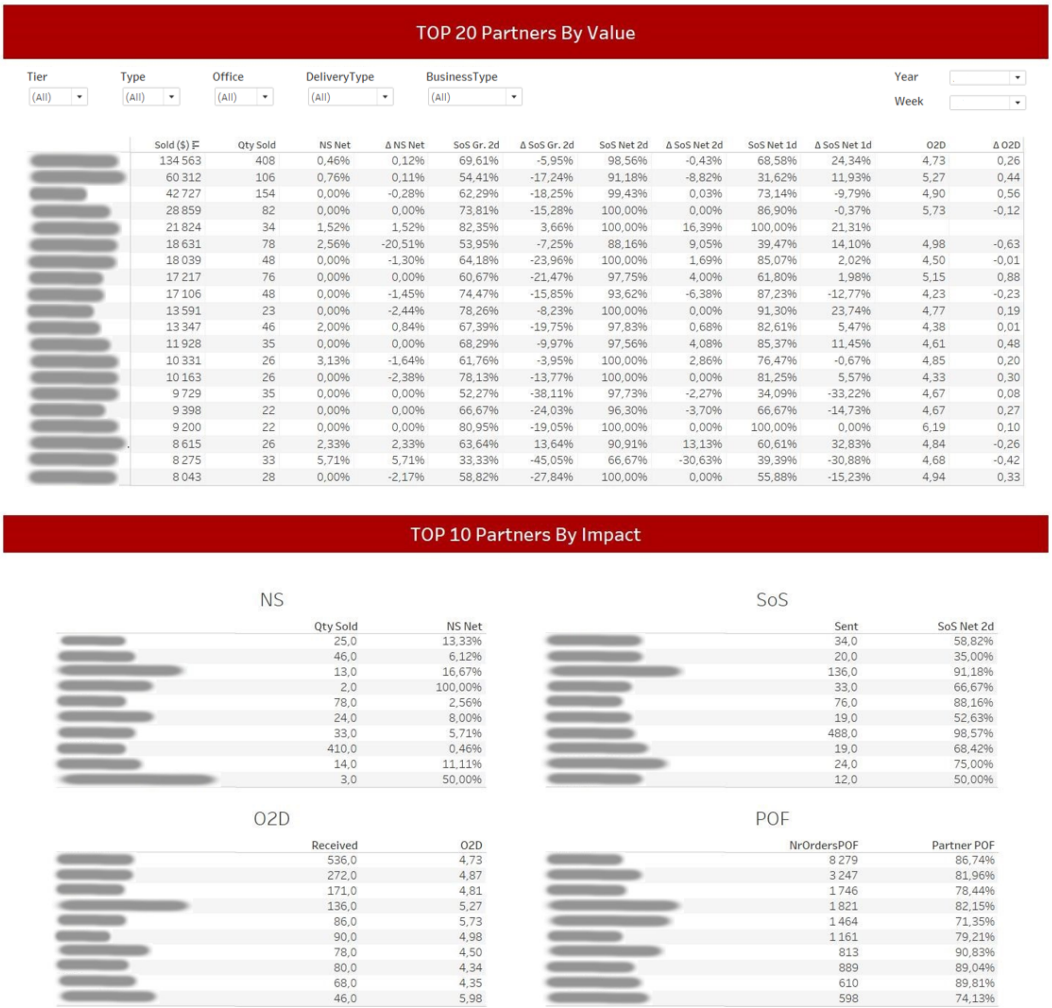
Figure 5.4: Dashboard view of the live pipeline status

A filtering by store name (and site name) is permitted and, moreover, a list of the top 20 partners with the most orders currently being processed is also shown. The view's lower half enables a deep dive on the order processing, combining both orders' age and ongoing step.

This view grants a quick and comprehensive insight on the pipeline's current status and permits the users to spot eventual problems.

5.4 TOP Partners by Impact

A further dashboard view was developed, presenting the selected week's top 20 partners by sold value, as well as their metrics' values and increase or decrease comparatively to the previous week, in the form of Δ. The same week's top 10 partners by impact per metric are also showed, with the impact being measured counting the number of out of target records, and, then, ranked. This dashboard view is presented in Figure 5.5.



TOP 20 Partners By Value

Tier (All) | Type (All) | Office (All) | DeliveryType (All) | BusinessType (All) | Year | Week

	Sold ($)	Qty Sold	NS Net	Δ NS Net	SoS Gr. 2d	Δ SoS Gr. 2d	SoS Net 2d	Δ SoS Net 2d	SoS Net 1d	Δ SoS Net 1d	O2D	Δ O2D
	134 563	408	0,46%	0,12%	69,61%	-5,95%	98,56%	-0,43%	68,58%	24,34%	4,73	0,26
	60 312	106	0,76%	0,11%	54,41%	-17,24%	91,18%	-8,82%	31,62%	11,93%	5,27	0,44
	42 727	154	0,00%	-0,28%	62,29%	-18,25%	99,43%	0,03%	73,14%	-9,79%	4,90	0,56
	28 859	82	0,00%	0,00%	73,81%	-15,28%	100,00%	0,00%	86,90%	-0,37%	5,73	-0,12
	21 824	34	1,52%	1,52%	82,35%	3,66%	100,00%	16,39%	100,00%	21,31%		
	18 631	78	2,56%	-20,51%	53,95%	-7,25%	88,16%	9,05%	39,47%	14,10%	4,98	-0,63
	18 039	48	0,00%	-1,30%	64,18%	-23,96%	100,00%	1,69%	85,07%	2,02%	4,50	-0,01
	17 217	76	0,00%	0,00%	60,67%	-21,47%	97,75%	4,00%	61,80%	1,98%	5,15	0,88
	17 106	48	0,00%	-1,45%	74,47%	-15,85%	93,62%	-6,38%	87,23%	-12,77%	4,23	-0,23
	13 591	23	0,00%	-2,44%	78,26%	-8,23%	100,00%	0,00%	91,30%	23,74%	4,77	0,19
	13 347	46	2,00%	0,84%	67,39%	-19,75%	97,83%	0,68%	82,61%	5,47%	4,38	0,01
	11 928	35	0,00%	0,00%	68,29%	-9,97%	97,56%	4,08%	85,37%	11,45%	4,61	0,48
	10 331	26	3,13%	-1,64%	61,76%	-3,95%	100,00%	2,86%	76,47%	-0,67%	4,85	0,20
	10 163	26	0,00%	-2,38%	78,13%	-13,77%	100,00%	0,00%	81,25%	5,57%	4,33	0,30
	9 729	35	0,00%	0,00%	52,27%	-38,11%	97,73%	-2,27%	34,09%	-33,22%	4,67	0,08
	9 398	22	0,00%	0,00%	66,67%	-24,03%	96,30%	-3,70%	66,67%	-14,73%	4,67	0,27
	9 200	22	0,00%	0,00%	80,95%	-19,05%	100,00%	0,00%	100,00%	0,00%	6,19	0,10
	8 615	26	2,33%	2,33%	63,64%	13,64%	90,91%	13,13%	60,61%	32,83%	4,84	-0,26
	8 275	33	5,71%	5,71%	33,33%	-45,05%	66,67%	-30,63%	39,39%	-30,88%	4,68	-0,42
	8 043	28	0,00%	-2,17%	58,82%	-27,84%	100,00%	0,00%	55,88%	-15,23%	4,94	0,33

TOP 10 Partners By Impact

NS

	Qty Sold	NS Net
	25,0	13,33%
	46,0	6,12%
	13,0	16,67%
	2,0	100,00%
	78,0	2,56%
	24,0	8,00%
	33,0	5,71%
	410,0	0,46%
	14,0	11,11%
	3,0	50,00%

SoS

	Sent	SoS Net 2d
	34,0	58,82%
	20,0	35,00%
	136,0	91,18%
	33,0	66,67%
	76,0	88,16%
	19,0	52,63%
	488,0	98,57%
	19,0	68,42%
	24,0	75,00%
	12,0	50,00%

O2D

	Received	O2D
	536,0	4,73
	272,0	4,87
	171,0	4,81
	136,0	5,27
	86,0	5,73
	90,0	4,98
	78,0	4,50
	80,0	4,34
	68,0	4,35
	46,0	5,98

POF

	NrOrdersPOF	Partner POF
	8 279	86,74%
	3 247	81,96%
	1 746	78,44%
	1 821	82,15%
	1 464	71,35%
	1 161	79,21%
	813	90,83%
	889	89,04%
	610	89,81%
	598	74,13%

Figure 5.5: View of the selected week's top partners by sold value and by impact per metrics

In this case, filtering is only possible - and necessary - by tier, type, office, delivery type and business type.

This dashboard view's aim is to understand which partners contribute the most for the business, and to evaluate their performance in a very concise way. The displayed set of KPIs is, therefore, centered on the partner: NS and SoS are two operational metrics, which have a limited connection to the customer. O2D is included to, precisely, give insight on the top partners' capability to meet Farfetch's requirements in terms of delivered customer experience.

A weekly metrics' visualization for the most important partners was already presented by the Supply Chain team before this project (see section 3.3).

5.5 Monthly Ops Cockpit

Six further views were developed 'exclusively' with the purpose of being presented in the monthly Ops Cockpit meeting, where each department presents their owned metrics. These views are totally independent from the others already presented.

As 'Fulfillment by Farfetch' is gaining more and more importance inside the company, each KPI is presented in three forms - grand total, FxFF and BaU. Lastly, the KPIs' evolution since beginning 2018 is presented, and compared with the company's annual target. If necessary, a further more detailed view is also provided.

The KPIs were grouped in six views, which are easily converted to slides to present in the referred meeting. All KPIs are presented in the same way, in order to facilitate visualization and comprehension. Figure 5.6 presents the monthly Ops Cockpit O2D slide; the remaining KPIs' views are presented in Appendix G.

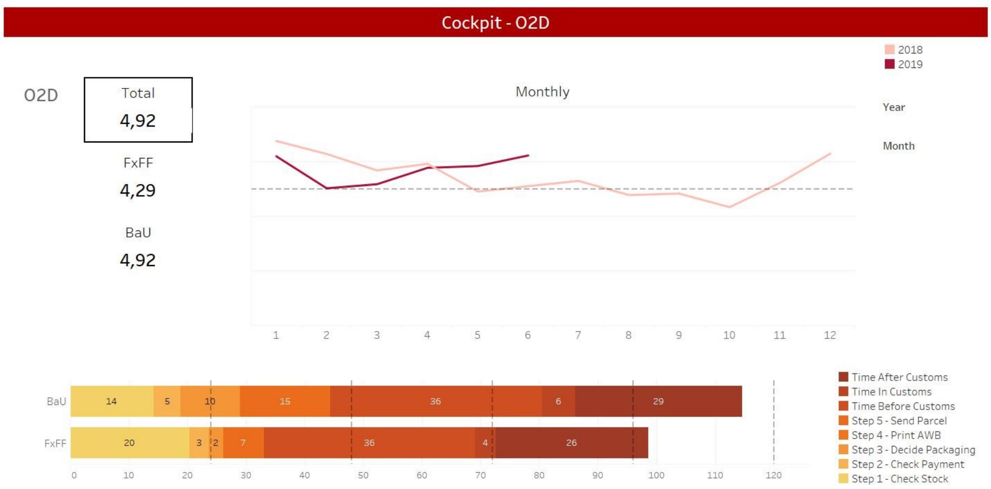


Figure 5.6: Cockpit - O2D

Chapter 6

Conclusion

6.1 Project Conclusions

As Supply Chain is a core part of Farfetch's business, in order to keep growing in a sustainable way, it is absolutely crucial to keep track of the end-to-end process and to collect, monitor and report all associated relevant information. Having a robust central monitoring and visualization tool is essential to enable appropriate and truthful visibility on the company's operations and to present official metrics to everyone (to avoid the existence of multiple 'minor' reports overlapping each other). This paves the way for proper reaction and further optimization.

Thus, the aim of this project was to develop a tool exhibiting the referred characteristics. Visibility on the entire end-to-end process has been achieved and, simultaneously, a redesign of already existent reporting routines in the Supply Chain has been performed, which resulted in their automation. The quest for consistency has required all monitoring and reporting methods to collect data from a single source and to be as automated as possible. At the same time, the company is turning towards a more customer-centric mindset, so the selected set of KPIs is supposed to assess processes based on their real impact on customer experience. Putting the customer at the core of the business is becoming Farfetch's key strategy and its enhancement the central criterion for project prioritization. In this line, new metrics - POF and NrRD - that manifest the real repercussion of Farfetch's operations on clients were created, in order to promote awareness to the quality of Farfetch's service as seen from the end user. For their meaning, they shall, together with O2D, be the center of future strategic efforts.

Important advancements have been made in terms of the visualization of O2D, which is an area in which the company intends to keep investing. Also, a better understanding of the correlation between O2D and shipping route was provided, which enables more accurate customer expectation management, for example through a more data driven EDD calculation.

Although the metric 'After Hours Orders' was not included in the final dashboard views, its creation was important to support the decisions on the FxFF business case and get insight on external to the business and consequential factors like customer behaviour.

This project has initiated the consolidation of Farfetch's KPIs' monitoring and internal communication of operational results. The online publishing of all reports makes information easily available to everyone. Although the obtained solution already represents a considerable improvement in the monitoring routines' unification around a single dataset, further efforts will be made in the future to achieve authentic and sincere visibility on the supply chain's process.

6.2 Future Work

Several opportunities have shown up during the elaboration of this project, which will be explored prospectively.

Regarding metrics' precision, both POF and NrRD can, in the future, encompass more conditions, such as the number of contacts with Customer Service (CS) or the paradigm that all return reasons are Farfetch's fault (except 'Changed my mind'). The After Hours metrics should also be elevated to a next level, as soon as more detailed data regarding the partners' working hours exists in the database. Ultimately, in favor of accuracy, Daylight Savings Time should also be incorporated in the calculation.

The customer segmentation should also be involved, as the company intends to add this filter to all KPIs and, therefore, gain new insight on how different customer classes are being satisfied.

The pipeline targets developed during this project are a first step of a major task - the goal was to provide a reference to benchmark the displayed values with. This complex task involves considerations relating to - among other - seasonality, partners' growth, the pipeline's capacity and the occurrence of special promotions and must be object of a deep reevaluation in the future. For this, time series are to be analyzed, in order to identify possible seasonality options and baselines. This challenging problem will require the use of Artificial Intelligence techniques to be able to be managed live. A Windows service, running in the background as long as Windows is running, is a possibility to consider in order to have constant data reading and refreshing. Also, regarding the number of orders in the pipeline, live observations on whether it is above or below expected must be made. This will allow Farfetch to warn stakeholders and partners of eventual problems that can be foreseen by the pipeline's status. Proactive alerts will be triggered if the threshold is exceeded or if a complication is detected.

Finally, the table refreshment must be optimized, in order not to overload the server. Therefore, one job shall be run at the beginning of each month, refreshing the complete queries. A second and lighter job must be run every day, keeping all the past rows and refreshing or adding just the ones created in the past two months.

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Appendix A

Business Process Modelling of All Steps

The figures presented in this Appendix illustrate the process swim lanes of all steps every order placed on Farfetch go through. The swim lane of the returns process is also presented.

Step 1

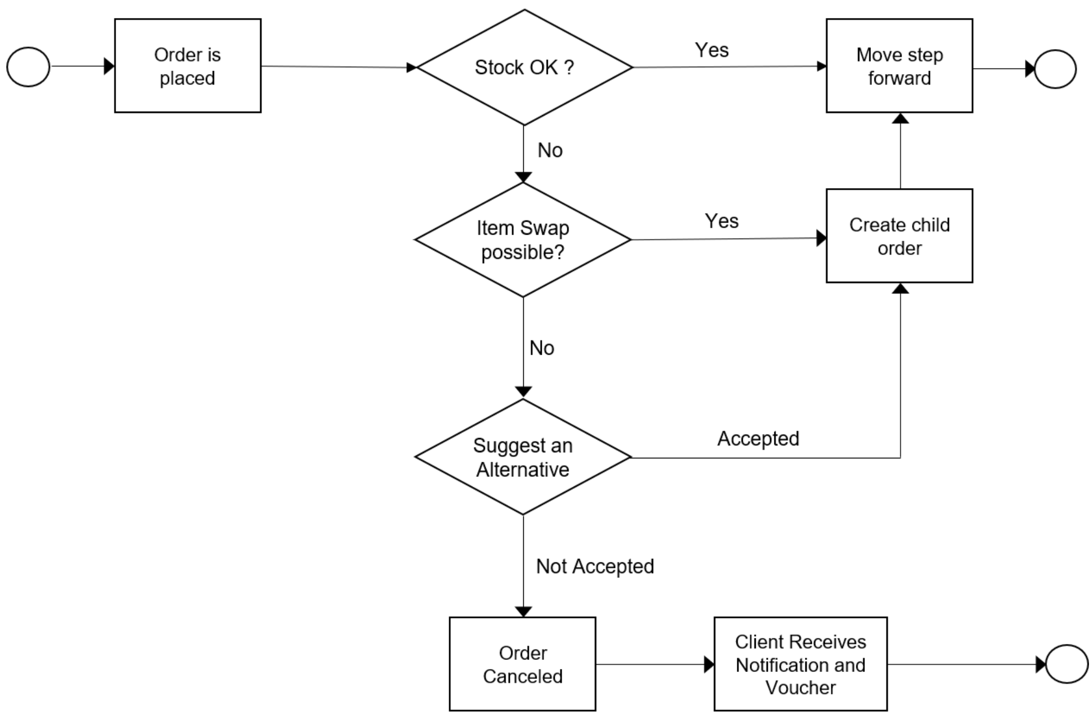

Figure A.1: Process Swimlane of Step 1

Step 2

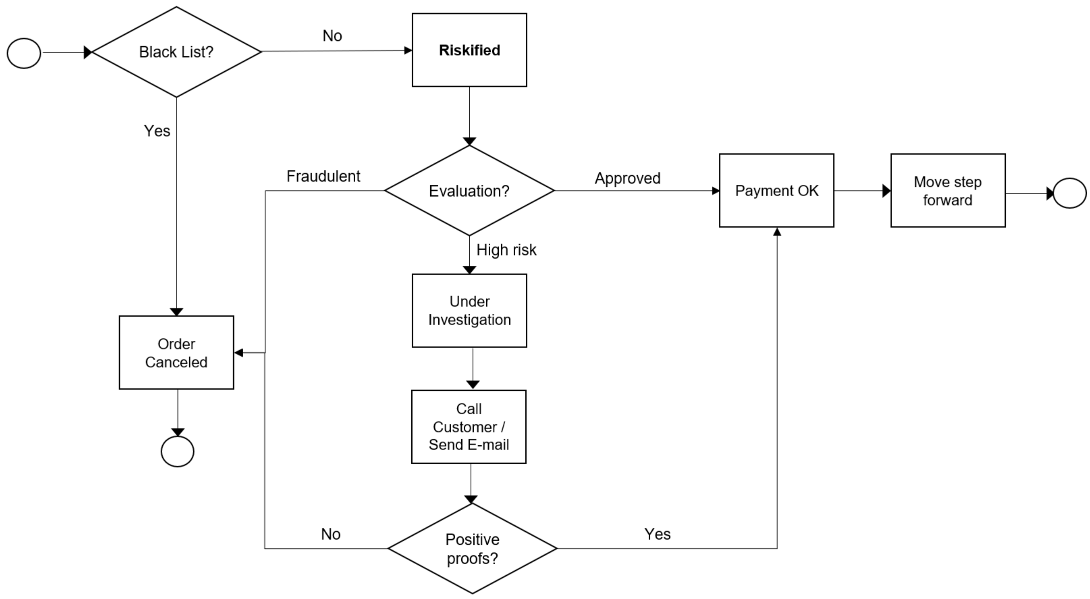

Figure A.2: Process Swimlane of Step 2

Step 3

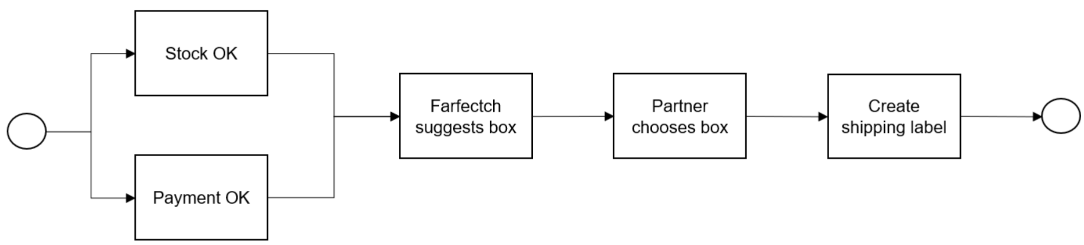

Figure A.3: Process Swimlane of Step 3

Step 4

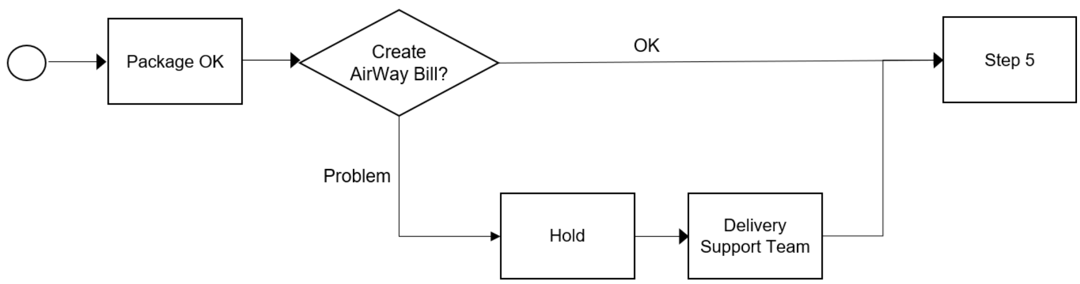

Figure A.4: Process Swimlane of Step 4

Step 5

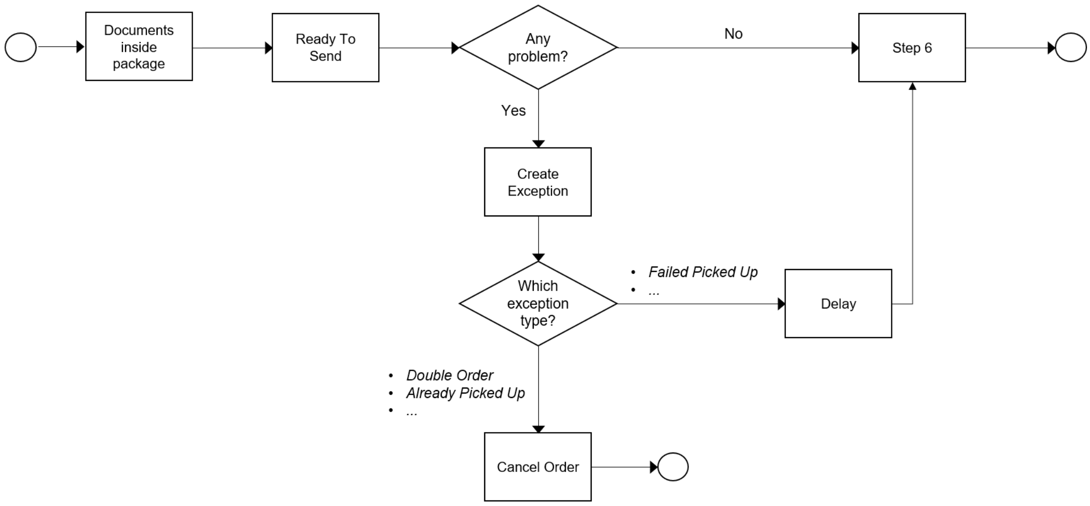

Figure A.5: Process Swimlane of Step 5

Step 6

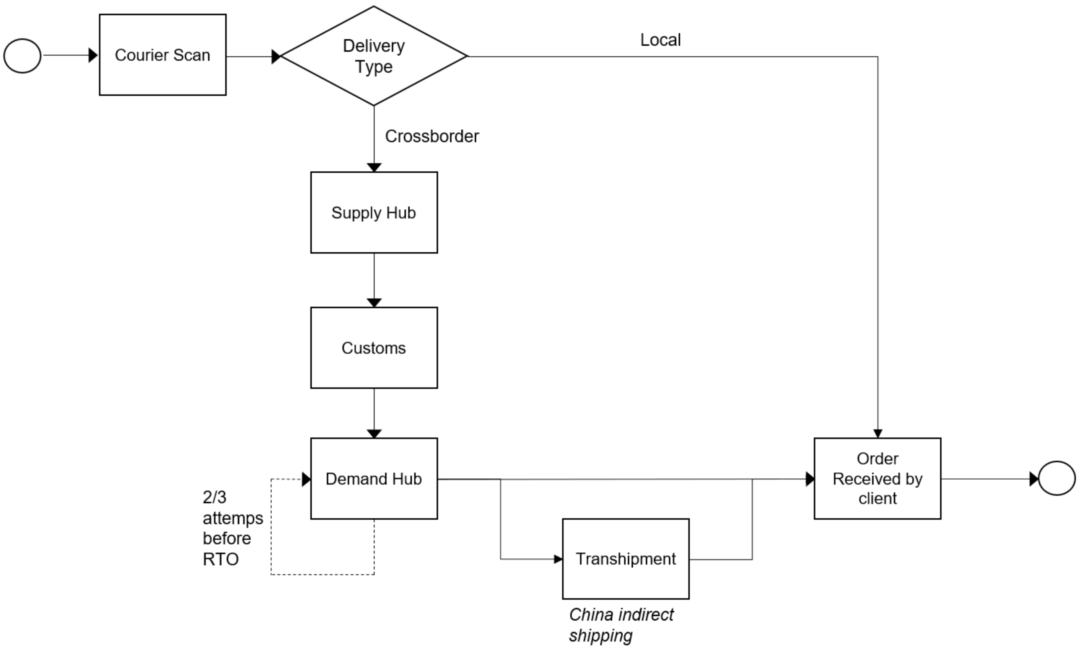

Figure A.6: Process Swimlane of Step 6

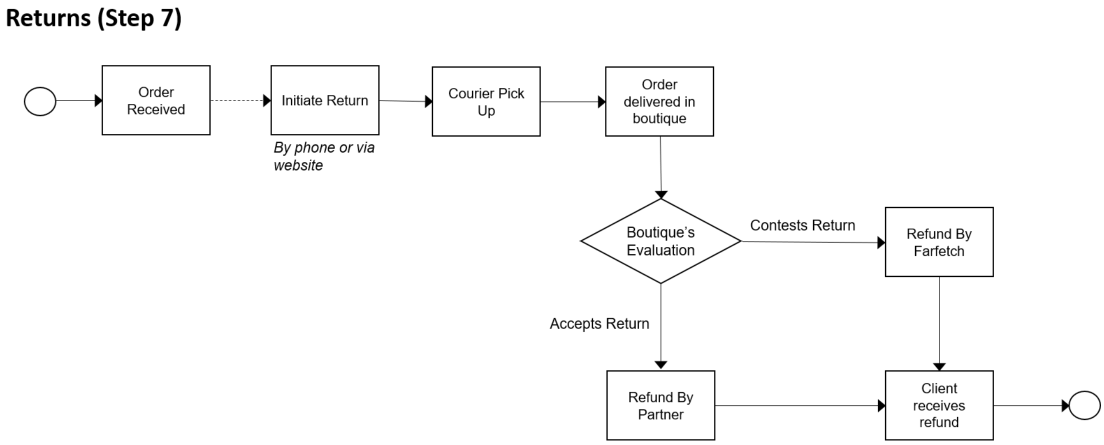

Figure A.7: Process Swimlane of Step 7

Appendix B

KPIs' Reference Sheet

In this Appendix, the reference sheet of all the in the dashboard views included KPIs are presented. Feature 'Filters' contains only the currently used filters, computed during the development of this project and available on the dashboard views. Other possible filter options, such as Customer Segment, were not included as they are not yet implemented.

The values showed in feature 'Target' correspond to Farfetch's annual global targets, but were blurred as they are confidential. Targets are also defined per tier, group and region - however, this project's scope is the monitoring of the whole company's metrics, which is why the global targets were used during the entire project.

Name	**Speed of Sending Net**
Identifier	SoS Net
Description	Time elapsed between order is placed and order is sent from boutique, excluding weekends, holidays and exceptions
Hardness	Hard
Calculation Rule	*SoS Net = [Time spent on 1 + Time Spent on step3 + Time Spent on step5] – [Time Spent on Weekends and Holidays + Time Spent on Hold]*
Value Type	Days
Filter	Store Region, Store Country, Customer Region, Customer Country, Type, Tier, Group, Office, Store Name, Site Name, Business Type, Delivery Type, New_Customer?
Frequency	Weekly, Monthly
Target	*None*
Status Options	*None*
Source of Data	SQL Server
Granularity	Product Order
Polarity	+
Measured Aspect	Duration
Audience	Operations, Partner Success

Figure B.1: SoS Net Reference Sheet

Name	**Speed of Sending Gross**
Identifier	SoS Gross
Description	Time elapsed between order is placed and order is sent from boutique
Hardness	Hard
Calculation Rule	*SoS Gross = Courier Scan Date – Order Creation Date*
Value Type	Days
Filter	Store Region, Store Country, Customer Region, Customer Country, Type, Tier, Group, Office, Store Name, Site Name, Business Type, Delivery Type, New_Customer?
Frequency	Weekly, Monthly
Target	*None*
Status Options	*None*
Source of Data	SQL Server
Granularity	Product Order
Polarity	+
Measured Aspect	Duration
Audience	Operations, Partner Success

Figure B.2: SoS Gross Reference Sheet

Name	**No Stock Net**
Identifier	NS Net
Description	Percentage of items canceled due to a lack of stock
Hardness	Hard
Calculation Rule	*NS Net = Number of Canceled by No Stock items / Total Number of Sent Orders*
Value Type	Percentage
Filter	Store Region, Store Country, Customer Region, Customer Country, Type, Tier, Group, Office, Store Name, Site Name, Business Type, Delivery Type, New_Customer?
Frequency	Weekly, Monthly
Target	[illegible]
Status Options	Above Target, Below Target
Source of Data	SQL Server
Granularity	Product Order
Polarity	-
Measured Aspect	Quality
Audience	Operations, Partner Success

Figure B.3: NS Net Reference Sheet

Name	**No Stock Gross**
Identifier	NS Gross
Description	Percentage of items canceled due to a lack of stock and accepted alternative suggestions
Hardness	Hard
Calculation Rule	*NS Gross = (Number of Canceled by No Stock Items + Suggest an Alternative Accepted) / Total Number of Sent Orders*
Value Type	Percentage
Filter	Store Region, Store Country, Customer Region, Customer Country, Type, Tier, Group, Office, Store Name, Site Name, Business Type, Delivery Type, New_Customer?
Frequency	Weekly, Monthly
Target	*None*
Status Options	*None*
Source of Data	SQL Server
Granularity	Product Order
Polarity	-
Measured Aspect	Quality
Audience	Operations, Partner Success

Figure B.4: NS Gross Reference Sheet

Name	**Transit Time**
Identifier	TT
Description	Time elapsed between order is scanned by courier and order is received at client's house (duration of step 6)
Hardness	Hard
Calculation Rule	*TT = Received Date – Sent Date*
Value Type	Days, Hours
Filter	Store Region, Store Country, Customer Region, Customer Country, Type, Tier, Group, Office, Store Name, Site Name, Business Type, Delivery Type, New_Customer?
Frequency	Weekly, Monthly
Target	*None*
Status Options	*None*
Source of Data	SQL Server, Carrier Logs
Granularity	Boutique Order
Polarity	-
Measured Aspect	Duration
Audience	Operations, Delivery

Figure B.5: Transit Time Reference Sheet

Name	**Speed of Sending Less Than 1 Day**
Identifier	SoS < 1d
Description	Percentage of orders that were sent in less than one day (24h)
Hardness	Hard
Calculation Rule	*SoS < 1d = Total Number of Orders with SoS < 24h / Total Number of Sent Orders*
Value Type	Percentage
Filter	Store Region, Store Country, Customer Region, Customer Country, Type, Tier, Group, Office, Store Name, Site Name, Business Type, Delivery Type, New_Customer?
Frequency	Weekly, Monthly
Target	[illegible]
Status Options	Above Target, Below Target
Source of Data	SQL Server
Granularity	Product Order
Polarity	+
Measured Aspect	Duration
Audience	Operations, Partner Success

Figure B.6: SoS Less Than 1 day Reference Sheet

Name	**Speed of Sending Less Than 2 Days**
Identifier	SoS < 2d
Description	Percentage of orders that were sent in less than two days (48h)
Hardness	Hard
Calculation Rule	*SoS < 2d = Total Number of Orders with SoS < 48h / Total Number of Sent Orders*
Value Type	Percentage
Filter	Store Region, Store Country, Customer Region, Customer Country, Type, Tier, Group, Office, Store Name, Site Name, Business Type, Delivery Type, New_Customer?
Frequency	Weekly, Monthly
Target	[illegible]
Status Options	Above Target, Below Target
Source of Data	SQL Server
Granularity	Product Order
Polarity	+
Measured Aspect	Duration
Audience	Operations, Partner Success

Figure B.7: SoS Less Than 2 days Reference Sheet

Name	**Order To Delivery Time**
Identifier	O2D
Description	Days elapsed between order is placed and order is received at client's house. Outliers are excluded
Hardness	Hard
Calculation Rule	*O2D = Received Date – Order Creation Date*
Value Type	Days
Filter	Store Region, Store Country, Customer Region, Customer Country, Type, Tier, Group, Office, Store Name, Site Name, Business Type, Delivery Type, New_Customer?
Frequency	Weekly, Monthly
Target	[illegible]
Status Options	Above Target, Below Target
Source of Data	SQL Server
Granularity	Product Order
Polarity	-
Measured Aspect	Duration
Audience	Operations, Delivery

Figure B.8: Order To Delivery Reference Sheet

Name	**Perfect Order Fulfillment**
Identifier	POF
Description	Percentage of all boutique orders that didn't have No Stock, arrived on Time and weren't returned due to Wrong Item
Hardness	Hard
Calculation Rule	*POF = Nr Perfect Orders / All Sent or Cancelled By No Stock Orders*
Value Type	Percentage
Filter	Store Region, Store Country, Customer Region, Customer Country, Type, Tier, Group, Office, Store Name, Site Name, Business Type, Delivery Type, New_Customer?
Frequency	Weekly, Monthly
Target	[illegible]
Status Options	Above Target, Below Target
Source of Data	SQL Server
Granularity	Boutique Order
Polarity	+
Measured Aspect	Quality
Audience	Operations

Figure B.9: SoS Gross Reference Sheet

Name	**Perfect Order Fulfillment – partner view**
Identifier	POF Partner
Description	Percentage of all boutique orders that didn't have No Stock, arrived on Time or Too Early and weren't returned due to Wrong Item
Hardness	Hard
Calculation Rule	*POF Partner = Nr Perfect Orders (considering Too Early as perfect) / All Sent or Cancelled By No Stock Orders*
Value Type	Percentage
Filter	Store Region, Store Country, Customer Region, Customer Country, Type, Tier, Group, Office, Store Name, Site Name, Business Type, Delivery Type, New_Customer?
Frequency	Weekly, Monthly
Target	*None*
Status Options	*None*
Source of Data	SQL Server
Granularity	Boutique Order
Polarity	+
Measured Aspect	Quality
Audience	Operations

Figure B.10: SoS Gross Reference Sheet

Name	**Nr of Ruined Days**
Identifier	#RD
Description	Sum of all days Farfetch ruined. Considers days with No Stock, Returns due to Wrong Item and deviation delivery days regarding the promised EDD
Hardness	Hard
Calculation Rule	*#RD = Nr No Stocks + Nr Returns (WI) + Nr Too Late Delivery days + Too Early Delivery days*
Value Type	Number
Filter	Store Region, Store Country, Customer Region, Customer Country, Type, Tier, Group, Office, Store Name, Site Name, Business Type, Delivery Type, New_Customer?
Frequency	Weekly, Monthly
Target	*None*
Status Options	Comparison To Week Before
Source of Data	SQL Server
Granularity	Product Order, Boutique Order
Polarity	-
Measured Aspect	Quality
Audience	Operations

Figure B.11: Number of Ruined Days Reference Sheet

Name	**Avg Days Ruined per Ruined Order**
Identifier	Avg. #RD
Description	Number of days an order ruined in average, if it wasn't perfect
Hardness	Hard
Calculation Rule	*Avg. #RD = Nr of Ruined Days / Nr of Ruined Boutique Orders*
Value Type	Number
Filter	Store Region, Store Country, Customer Region, Customer Country, Type, Tier, Group, Office, Store Name, Site Name, Business Type, Delivery Type, New_Customer?
Frequency	Weekly, Monthly
Target	*None*
Status Options	*None*
Source of Data	SQL Server
Granularity	Product Order, Boutique Order
Polarity	-
Measured Aspect	Quality
Audience	Operations

Figure B.12: Average Ruined Days per Ruined Order Reference Sheet

Name	**After Hours Orders**
Identifier	AHO
Description	Percentage of orders placed outside the partners' labor hours
Hardness	Hard
Calculation Rule	*AHO = Orders placed between 9h and 18h (partners' time zone), except on weekends / All orders placed*
Value Type	Percentage
Filter	Store Region, Store Country, Customer Region, Customer Country, Type, Tier, Group, Office, Store Name, Site Name, Business Type, Delivery Type, New_Customer?
Frequency	Weekly, Monthly
Target	*None*
Status Options	*None*
Source of Data	SQL Server, API Mapbox
Granularity	Product Order
Polarity	-
Measured Aspect	Capacity
Audience	Operations, Partner Success, Fulfillment Operations

Figure B.13: After Hours Orders Reference Sheet

Name	**Forecast Accuracy All Farfetch**
Identifier	FA Farfetch
Description	Comparison between a week's sales and the sales forecast performed 4 weeks earlier, for the company as a whole
Hardness	Hard
Calculation Rule	$FA\ Farfetch = 1- \sum \sum MAPE,\ i = 1,\dots,7;\ p = 1,\dots,P$
Value Type	Percentage
Filter	-
Frequency	Weekly
Target	[illegible]
Status Options	Above Target, Below Target
Source of Data	SQL Server
Granularity	Does Not Apply
Polarity	+
Measured Aspect	Does Not Apply
Audience	Operations, Marketing, Parter Success

Figure B.14: Forecast Accuracy whole Farfetch Reference Sheet

Name	**Forecast Accuracy By Partner**
Identifier	FA Partner
Description	Comparison between a week's sales and the sales forecast performed 4 weeks earlier, by partner
Hardness	Hard
Calculation Rule	$FA\ Partner = 1- \sum MAPE,\ i = 1,\dots 7$
Value Type	Percentage
Filter	-
Frequency	Weekly
Target	[illegible]
Status Options	Above Target, Below Target
Source of Data	SQL Server
Granularity	Does Not Apply
Polarity	+
Measured Aspect	Does Not Apply
Audience	Operations, Marketing, Parter Success

Figure B.15: Forecast Accuracy per Partner Reference Sheet

Name	**Percentage of Returns**
Identifier	Returns %
Description	Percentage of all delivered orders that were returned
Hardness	Hard
Calculation Rule	*% Returns = Total Number of Returned Orders / Total Number of Received Orders*
Value Type	Percentage
Filter	Store Region, Store Country, Customer Region, Customer Country, Type, Tier, Group, Office, Store Name, Site Name, Business Type, Delivery Type, New_Customer?
Frequency	Weekly, Monthly
Target	*None*
Status Options	*None*
Source of Data	SQL Server
Granularity	Product Order
Polarity	-
Measured Aspect	Customer Satisfaction
Audience	Operations

Figure B.16: Percentage of Returns Reference Sheet

Name	**Orders in Pipeline**
Identifier	OiP
Description	Current number of orders being processed
Hardness	Hard
Calculation Rule	*OiP = Nr Orders Step 1 + Nr Orders Step 2 + Nr Orders Step 3 + Nr Orders Step 4 + Nr Orders Step 5*
Value Type	Integer
Filter	Store Region, Store Country, Type, Tier, Group, Office, Store Name, Age of Order
Frequency	Live
Target	*None*
Status Options	*None*
Source of Data	SQL Server
Granularity	Boutique Order
Polarity	Does Not Apply
Measured Aspect	Capacity
Audience	Operations, Logistics

Figure B.17: Number of Orders in Pipeline Reference Sheet

Name	**Avg Age of Orders in Pipeline**
Identifier	OiP Avg. Age
Description	Average age of all orders currently being processed
Hardness	Hard
Calculation Rule	*OiP Avg. Age = (Current Date – Order Creation Date) / OiP*
Value Type	Days
Filter	Store Region, Store Country, Type, Tier, Group, Office, Store Name, Age of Order
Frequency	Live
Target	*None*
Status Options	*None*
Source of Data	SQL Server
Granularity	Boutique Order
Polarity	Does Not Apply
Measured Aspect	Capacity, Duration
Audience	Operations, Logistics

Figure B.18: Average Age of Orders in Pipeline Reference Sheet

Name	**Time Spent in Step 1**
Identifier	Avg. Step 1
Description	Average time an order takes in step 1 (Check Stock)
Hardness	Hard
Calculation Rule	*Avg. Step 1 = Stock OK Date – Order Creation Date*
Value Type	Absolute
Filter	Store Region, Store Country, Customer Region, Customer Country, Type, Tier, Group, Office, Store Name, Site Name, Business Type, Delivery Type, New_Customer?
Frequency	Weekly, Monthly
Target	*None*
Status Options	*None*
Source of Data	SQL Server
Granularity	Product Order
Polarity	-
Measured Aspect	Duration
Audience	Operations, Fulfillment Operations

Figure B.19: Average Time Spent in Step 1 Reference Sheet

Name	**Time Spent in Step 2**
Identifier	Avg. Step 2
Description	Average time an order takes in step 2 (Check Payment)
Hardness	Hard
Calculation Rule	*Avg. Step 2 = Payment OK Date – Order Creation Date*
Value Type	Absolute
Filter	Store Region, Store Country, Customer Region, Customer Country, Type, Tier, Group, Office, Store Name, Site Name, Business Type, Delivery Type, New_Customer?
Frequency	Weekly, Monthly
Target	*None*
Status Options	*None*
Source of Data	SQL Server
Granularity	Product Order
Polarity	-
Measured Aspect	Duration
Audience	Operations, Fulfillment Operations

Figure B.20: Average Time Spent in Step 2 Reference Sheet

Name	**Time Spent in Step 3**
Identifier	Avg. Step 3
Description	Average time an order takes in step 3 (Decide Packaging)
Hardness	Hard
Calculation Rule	*Avg. Step 3 = Packaging OK Date – max[Stock OK Date, Payment OK Date]*
Value Type	Absolute
Filter	Store Region, Store Country, Customer Region, Customer Country, Type, Tier, Group, Office, Store Name, Site Name, Business Type, Delivery Type, New_Customer?
Frequency	Weekly, Monthly
Target	*None*
Status Options	*None*
Source of Data	SQL Server
Granularity	Product Order
Polarity	-
Measured Aspect	Duration
Audience	Operations, Fulfillment Operations

Figure B.21: Average Time Spent in Step 3 Reference Sheet

Name	**Time Spent in Step 4**
Identifier	Avg. Step 4
Description	Average time an order takes in step 4 (Print Shipping Label)
Hardness	Hard
Calculation Rule	*Avg. Step 4 = Ready To Send Date – Decide Packaging Date*
Value Type	Absolute
Filter	Store Region, Store Country, Customer Region, Customer Country, Type, Tier, Group, Office, Store Name, Site Name, Business Type, Delivery Type, New_Customer?
Frequency	Weekly, Monthly
Target	*None*
Status Options	*None*
Source of Data	SQL Server
Granularity	Product Order
Polarity	-
Measured Aspect	Duration
Audience	Operations, Fulfillment Operations

Figure B.22: Average Time Spent in Step 4 Reference Sheet

Name	**Time Spent in Step 5**
Identifier	Avg. Step 5
Description	Average time an order takes in step 5 (Send Parcel)
Hardness	Hard
Calculation Rule	*Avg. Step 5 = Send Date – Ready To Send Date*
Value Type	Absolute
Filter	Store Region, Store Country, Customer Region, Customer Country, Type, Tier, Group, Office, Store Name, Site Name, Business Type, Delivery Type, New_Customer?
Frequency	Weekly, Monthly
Target	*None*
Status Options	*None*
Source of Data	SQL Server
Granularity	Product Order
Polarity	-
Measured Aspect	Duration
Audience	Operations, Fulfillment Operations

Figure B.23: Average Time Spent in Step 5 Reference Sheet

Appendix C

Description of all tables feeding the dashboard and the query for their assembly

Both the included data description and the respective queries of all tables created in SQL to feed data to the visualization software are presented in this Appendix.

C.1 BI_ANALYTICS.dbo.SCA_Scorecard

This SQL table includes the following data (columns), collected from multiple tables within Farfetch's database and aggregated making use of four subtables. The identification - and a brief description - of each column of the final table is provided next.

When nothing is said, metrics are measured Gross.

- **OrderLineID** - Identification of a Product Order;
- **TenantID** - Identification of the origin of the order (Farfetch.com, Black&White);
- **OrderSiteID** - Identification of a Portal Order;
- **OrderCodeID** - Identification of a Boutique Order;
- **OrderCode** - Portal Order identification code the client receives by e-mail;
- **OrderDate_GMT** - Order's creation date (GMT);
- **Timezone** - Partners' stock point time zone (name);
- **OrderDate_PartnerTMZ** - Order's creation date in the partner's time zone;
- **CreatedHour_PartnerTMZ** - Order's creation hour in the partner's time zone;
- **ProductID** - Identification of the ordered product;
- **StoreKey** - Unique Partner Identifier;
- **LocalID** - Unique Site Identifier;
- **StoreName** - Self explanatory;

- **SiteName** - Self explanatory;
- **Tier** - Self Explanatory;
- **Group** - Self Explanatory;
- **Type** - Information whether partner is a boutique or a brand;
- **Office** - Information of which FF office supports the partner;
- **StoreRegion** - Identification of the region where the partner is located;
- **StoreCountryID** - Unique identifier of the partner's country;
- **StoreCountry** - Identification of the country where the store is located;
- **StoreCity** - Identification of the city where the store is located;
- **UserID** - Client's unique identifier;
- **NewCustomer?** - Binary description whether it is the customer's first purchase;
- **CustomerRegion** - Identification of the shipping destination region;
- **CustomerCountryID** - Unique identifier of the shipping country;
- **CustomerCountry** - Identification of the shipping destination country;
- **CustomerCity** - Identification of the shipping destination city;
- **ShipRoute** - Self Explanatory;
- **DeliveryType** - Information whether order shipment is 'Crossborder', 'Domestic' or 'IntraEu';
- **Value** - Product Order value ($) without shipping costs;
- **BusinessType** - Information whether shipment is made through 'FxFF', 'BaU' or 'Fashion Concierge';
- **FxFF** - Binary variable;
- **Regular** - Binary variable;
- **FashionConcierge** - Binary variable;
- **Year_Created** - Self Explanatory;
- **Quarter_Created** - Self Explanatory;
- **Month_Created** - Self Explanatory;
- **Week_Created** - Self Explanatory;
- **Year_NS** - Self Explanatory;
- **Quarter_NS** - Self Explanatory;
- **Month_NS** - Self Explanatory;
- **Week_NS** - Self Explanatory;
- **Year_Sent** - Self Explanatory;
- **Quarter_Sent** - Self Explanatory;

- **Month_Sent** - Self Explanatory;
- **Week_Sent** - Self Explanatory;
- **Year_Received** - Self Explanatory;
- **Quarter_Received** - Self Explanatory;
- **Month_Received** - Self Explanatory;
- **Week_Received** - Self Explanatory;
- **Year_Returned** - Self Explanatory;
- **Quarter_Returned** - Self Explanatory;
- **Month_Returned** - Self Explanatory;
- **Week_Returned** - Self Explanatory;
- **CancelDate** - Product Order's cancellation date Identification of a Product Order;
- **CancelNoStockDate** - Product Order's cancellation date, due to a No Stock occurrence;
- **NS_Eval_Date** - Product Order's No Stock Evaluation Date;
- **Cancelled** - Binary identification whether Product Order was cancelled;
- **Delivered** - Binary identification whether Product Order was delivered;
- **Returned** - Binary identification whether Product Order was returned;
- **HasDailyPickUp** - INformation whether partner has daily pickup;
- **AfterHoursOrders** - Binary identification whether Product Order was placed outside partner's working hours;
- **ReadyAfterPickup** - Binary identification whether Boutique Order wasn't ready to sent at the daily pickup time, is only referred to partners with daily pick up;
- **HadNoStock** - Self Explanatory;
- **IsItemSwapParent** - Binary identification whether Product Order is an item swap parent;
- **IsItemSwapChild** - Binary identification whether Product Order is an item swap child;
- **SaA** - Information whether the Product Order gave rise to a 'Suggest an Alternative' occurrence;
- **SaA_Decision** - 'Suggest an Alternative' outcome;
- **FF_Fault** - Data regarding whether 'No Stock' occurrence was Farfetch's fault (e.g. deficient stock integration);
- **NS_Net** - Binary identification whether Product Order increases the NS Net metric;
- **NS_Gross** - Binary identification whether Product Order increases the NS Gross metric;
- **NewCust_NS_Net** - Binary identification whether Product Order increases the NS Net metric for new customers;
- **NewCust_NS_Gross** - Binary identification whether Product Order increases the NS Gross metric for new customers;

- **SoS_hours_Net** - Self Explanatory;
- **SoS_days_Net** - Self Explanatory;
- **SoS_Net_1d** - Binary identification whether Product Order's SoS is less than one day;
- **SoS_Net_2d** - Binary identification whether Product Order's SoS is less than two days;
- **SoS_hours** - Self Explanatory;
- **SoS_days** - Self Explanatory;
- **TT_hours** - Self Explanatory;
- **TT_days** - Self Explanatory;
- **LeadTime_hours** - Self Explanatory;
- **LeadTime_days** - Self Explanatory;
- **EDD_CheckOut** - Information on the delivery's time accuracy towards the EDD sent by e-mail;
- **DeliveryOutlier?** - Binary variable on whether a Product Order shall be considered as an outlier and excluded of certain calculations;
- **NoStock?** - Binary information on whether at most one product within a boutique order had a No Stock occurrence;
- **TooEarly?** - Binary information on whether at most one product within a boutique order was delivered too early;
- **TooLate?** - Binary information on whether at most one product within a boutique order was delivered too late;
- **WrongItem?** - Binary information on whether at most one product within a boutique order was returned due to a wrong item;
- **IsPOF?** - Binary information on whether a Product Order is to be considered perfect;
- **Step0_CreatedDate_GMT** - Order Creation date;
- **Step1_StockOK_GMT** - End of Step 1 date;
- **Step2_PaymentOK_GMT** - End of Step 2 date;
- **Step3_PackagingOK_GMT** - End of Step 3 date;
- **Step4_ReadyToSend_GMT** - End of Step 4 date;
- **Step5_OrderPickup_GMT** - End of Step 5 date (send date);
- **Step6_Received_GMT** - End of Step 6 date (delivery date);
- **TimeSpent_Step1_hours** - Self Explanatory;
- **TimeSpent_Step2_hours** - Self Explanatory;
- **TimeSpent_Step3_hours** - Self Explanatory;
- **TimeSpent_Step4_hours** - Self Explanatory;
- **TimeSpent_Step5_hours** - Self Explanatory;

- **TimeSpent_Step6_hours** - Self Explanatory, equivalent to Transit Time;
- **TimeSpent_Step1_Net** - Self Explanatory;
- **TimeSpent_Step3_Net** - Self Explanatory;
- **HasCustoms?** - Binary information on whether article has to go through Customs;
- **TimeBeforeCustoms** - Self Explanatory;
- **TimeInCustoms** - Self Explanatory;
- **TimeAfterCustoms** - Self Explanatory;
- **TimeInTransit** - Total Transit Time for items, which don't have to go through in Customs;
- **ReturnReason** - Information on the return reason, as stated by the customer;
- **ReturnReasonDefault** - Rearrangement of return reasons in organized groups;
- **ReturnReceivedDate** - Partner's receiving of the returned item date;
- **ReturnEvaluationDate** - Assessment whether returned iem is accepted or contested by the partner date;
- **RefundByWho** - Information on which entity performs the client's refund (Farfetch or the partner);
- **RefundDate** - Self Explanatory.

SQL query originating table BI_ANLYTICS.DBO.SCORECARD

```sql
------------------- Set Monday as starting week day
SET DATEFIRST 1
drop table if exists #Overview
select ord.OrderLineId
, ord.TenantID
, ord.OrderSiteID
, ord.OrderCodeID
, ord.OrderCode
, ord.OrderDate_GMT
, prod.ProductID
, store.StoreKey
, store.LocalID
, store.StoreName
, store.SiteName
, suc.Tier as Tier
, suc.[Group]
, suc.[Type]
, suc.Office
, ord.UserID
, case when ord.OrderDate_GMT = u.FirstPurchaseDate then 1 else 0
 ↪ end as [NewCustomer?]
, geostore.RegionCustomerFF as StoreRegion
, geostore.PaisID as StoreCountryID
```

```
, geostore.Country as StoreCountry
, geostore.City as StoreCity
, geo.RegionCustomerFF as CustomerRegion
, geo.PaisID as CustomerCountryID
, geo.Country as CustomerCountry
, geo.City as CustomerCity
, case when geostore.Country = geo.Country then 'Domestic'
    when geostore.ZonaEuro = 'Yes' and geo.ZonaEuro = 'Yes' then
     ↪ 'Intra-EU'
    else 'Crossborder' end as DeliveryType
, ord.ValueWithoutShip_Store_USD as [Value]
, case when ord.CancelNoStockDate is not null then 1
    when ord.OtherCancellationsDate is not null then 1
    when ord.CancelDate is not null then 1
    else 0 end as Cancelled
, case when ord.ReceivedDate is not null then 1
    else 0 end as Delivered
, case when ord.ReturnReason <> '-2' then 1
    else 0 end as Returned
into #Overview
from [BI_DW].[dbo].FactOrdersLines ord
inner join [BI_DW].[dbo].DimProduct prod on ord.SK_Product =
 ↪ prod.SK_Product
inner join [BI_DW].[dbo].DimStore store on
 ↪ ord.sk_store=store.SK_Store
inner join [BI_DW].[dbo].DimGeography geo on ord.SK_GeographyBill =
 ↪ geo.SK_Geography
inner join [BI_DW].[dbo].DimGeography geostore on
 ↪ geostore.SK_Geography = store.SK_StoreAddress
inner join [BI_ANALYTICS].[dbo].Success_Segments suc on
 ↪ suc.StoreKey = store.StoreKey
left join [BI_DW].[dbo].DimUser u on ord.SK_User = u.SK_User
where YEAR(ord.OrderDate_GMT) >= 2018
        and ord.TenantId = 10000

drop table if exists #AddInfoStore
select ord.OrderLineId
, ord.TenantID
, ord.OrderSiteID
, ord.OrderCodeID
, store.LocalID as StoreID
, store.StoreName
, store.SiteName
, store1.BusinessType
, case when store1.BusinessType = 'FF Warehouse' then 1 else 0 end
 ↪ as FxFF
```

```
, case when store1.BusinessType = 'Regular' then 1 else 0 end as
  ↪ Regular
, case when store1.BusinessType = 'Fashion Concierge' then 1 else 0
  ↪ end as FashionConcierge
, store.HasStockSync
, store.HasDailyPickup
, store.PickupHour
, ord.OrderDate_GMT
, DATEADD(HOUR, tmz.Offset_float, ord.OrderDate_GMT) as
  ↪ OrderDate_PartnerTMZ
, DATEPART(hour, DATEADD(HOUR, tmz.Offset_float,
  ↪ ord.OrderDate_GMT)) as CreatedHour_PartnerTMZ
, tmz.Timezone
, tmz.Offset
, tmz.DST_Offset
, case when d.DayOfWeekNumber in (6,7) then 1
    when datepart(hour, ord.OrderDate_GMT) + tmz.Offset_float not
      ↪ between 9 and 18 then 1
    else 0 end as AfterHoursOrder
, strat.Step4_ReadyToSend_StoreTZ as Ready2SendDate
, case when store.HasDailyPickup = 'Yes' and
  ↪ DATEPART(hour,strat.Step4_ReadyToSend_StoreTZ) >
  ↪ store.PickupHour then 1
    when store.HasDailyPickup = 'Yes' and
      ↪ DATEPART(hour,strat.Step4_ReadyToSend_StoreTZ) =
      ↪ store.PickupHour and
      ↪ DATEPART(minute,strat.Step4_ReadyToSend_StoreTZ) > '15'
      ↪ then 1
    when store.HasDailyPickup = 'No' then NULL
    else 0 end as ReadyAfterPickUp
into #AddInfoStore
from [BI_DW].[dbo].FactOrdersLines ord
inner join [BI_DW].[dbo].DimDate d on d.sk_date=
  ↪ ord.SK_OrderDate_TZGMT
inner join [BI_DW].[dbo].DimStore store on
  ↪ ord.sk_store=store.SK_Store
inner join [BI_DW].[dbo].DimStore store1 on
  ↪ ord.StoreKey=store1.LocalID
left join bixpl.[ANALYSTS].[dbo].[OPS_Strat_Times] strat on
  ↪ ord.OrderCodeId = strat.BoutiqueOrder
where YEAR(ord.OrderDate_GMT) >= 2018
        and ord.TenantId = 10000
        and store1.rowexcludedate is null

drop table if exists #KPIs
select ord.OrderLineId
```

```
, ord.OrderSiteID
, ord.OrderCodeID
, ord.HadNoStock
, case when ord.IsItemSwapParent = 'Yes' then 1 else 0 end as
 ↪ IsItemSwapParent
, case when ord.IsItemSwapParent = 'No' then 1 else 0 end as
 ↪ IsItemSwapChild
, ord.HasSuggestionAlternative as SaA
, case when ord.SuggestionAlternativeStatus = 'Successful' or
 ↪ ord.SuggestionAlternativeStatus = 'Unsuccessful' then
 ↪ ord.SuggestionAlternativeStatus
   when ord.HasSuggestionAlternative = 'No' then null
   else 'NoData' end as SaA_Decision
, case when ord.CancelNoStockDate is not null and aux.OrderPortalId
 ↪ = ord.OrderPortalId then 'Yes'
   when ord.CancelNoStockDate is null then null
   else 'No' end as FF_Fault
, case when ord.CancelNoStockDate is not null and (case when
 ↪ ord.CancelNoStockDate is not null and aux.OrderPortalId =
 ↪ ord.OrderPortalId then 'Yes'
   when ord.CancelNoStockDate is null then null else 'No' end) =
    ↪ 'No' then 1
   else 0 end as NS_Net
, case when ord.CancelNoStockDate is not null or
 ↪ ord.SuggestionAlternativeStatus = 'Successful' then 1
   else 0 end as NS_Gross
, CONVERT(decimal(8,2),ord.SoS_withoutWeekendsHolds_days*24.0) as
 ↪ SoS_hours_Net
, ord.SoS_withoutWeekendsHolds_days as SoS_days_Net
, case when ord.CancelDate is null then
 ↪ ord.IsSOSNetLessThan1DayWithExceptions
   else null end as SoS_Net_1d
, case when ord.CancelDate is null then
 ↪ ord.IsSOSNetLessThan2DayWithExceptions
   else null end as SoS_Net_2d
, strat.SpeedofSending_hours as SoS_hours
, CONVERT(decimal(6,2), strat.SpeedofSending_hours/24.0) as
 ↪ SoS_days
, strat.TimeSpent_Step6_hours as TT_hours
, CONVERT(decimal(8,2), strat.TimeSpent_Step6_hours/24.0) as
 ↪ TT_days
, strat.LeadTime_hours as LeadTime_hours
, CONVERT(decimal(8,2), strat.LeadTime_hours/24.0) as LeadTime_days
, pof.[NoStock?]
, pof.[TooEarly?]
, pof.[TooLate?]
```

```
, pof.ReturnWI as [WrongItem?]
, pof.POF as [IsPOF?]
, pof.POF_PartnerView as [POF_Partner?]
, rd.SK_User as UserID
, rd.RuinedClient
, rd.NrRuinedDays
into #KPIs
from [BI_DW].[dbo].FactOrdersLines ord
inner join [BI_DW].[dbo].DimStore store on
 ↪ ord.sk_store=store.SK_Store
left join bixpl.[ANALYSTS].[dbo].[OPS_Strat_Times] strat on
 ↪ ord.OrderCodeId = strat.BoutiqueOrder
left join bixpl.[ANALYSTS].[dbo].[z_BI_AuxNoStockFFFault] aux on
 ↪ ord.OrderPortalId = aux.OrderPortalId
left join [BI_ANALYTICS].[dbo].SCA_JF_POF_JP pof on ord.OrderCodeId
 ↪ = pof.OrderCodeId
left join [BI_ANALYTICS].[dbo].SCA_JF_RD_Orderline rd on
 ↪ ord.orderlineid = rd.OrderLineId
where YEAR(ord.OrderDate_GMT) >= 2018
        and ord.TenantId = 10000

drop table if exists #AllDates
select ord.OrderLineId
, ord.OrderSiteID
, ord.OrderCodeID
, ord.OrderDate_GMT
, ord.BoutiqueOrderDate
, DATEPART(year, ord.OrderDate_GMT) as Year_Created
, DATEPART(quarter, ord.OrderDate_GMT) as Quarter_Created
, DATEPART(month, ord.OrderDate_GMT) as Month_Created
, DATEPART(week, ord.OrderDate_GMT) as Week_Created
, DATEPART(year, ord.DateNoStockEval) as Year_NS
, DATEPART(quarter, ord.DateNoStockEval) as Quarter_NS
, DATEPART(month, ord.DateNoStockEval) as Month_NS
, DATEPART(week, ord.DateNoStockEval) as Week_NS
, DATEPART(year, ord.DateStep5_DHL_GMT) as Year_Sent
, DATEPART(quarter, ord.DateStep5_DHL_GMT) as Quarter_Sent
, DATEPART(month, ord.DateStep5_DHL_GMT) as Month_Sent
, DATEPART(week, ord.DateStep5_DHL_GMT) as Week_Sent
, DATEPART(year, ord.ReceivedDate_GMT) as Year_Received
, DATEPART(quarter, ord.ReceivedDate_GMT) as Quarter_Received
, DATEPART(month, ord.ReceivedDate_GMT) as Month_Received
, DATEPART(week, ord.ReceivedDate_GMT) as Week_Received
, DATEPART(year, ord.ReturnReceivedDate) as Year_Returned
, DATEPART(quarter, ord.ReturnReceivedDate) as Quarter_Returned
, DATEPART(month, ord.ReturnReceivedDate) as Month_Returned
```

```
, DATEPART(week, ord.ReturnReceivedDate) as Week_Returned
, case when ord.CancelNoStockDate is not null then 1
    when ord.OtherCancellationsDate is not null then 1
    when ord.CancelDate is not null then 1
    else 0 end as Cancelled
, ord.CancelDate
, ord.CancelNoStockDate
, ord.DateNoStockEval as NS_Eval_Date
, ord.OtherCancellationsDate
, ord.SendDate
, ord.ReceivedDate_GMT
, case when ord.ReceivedDate is not null then 1
    else 0 end as Delivered
, strat.Step0_CreatedDate_GMT
, strat.Step1_StockOK_GMT
, strat.Step2_PaymentOK_GMT
, strat.Step3_PackagingOK_GMT
, strat.Step4_ReadyToSend_GMT
, strat.Step5_OrderPickup_GMT
, strat.Step6_Received_GMT
, strat.TimeSpent_Step1_hours
, strat.TimeSpent_Step2_hours
, strat.TimeSpent_Step3_hours
, strat.TimeSpent_Step4_hours
, strat.TimeSpent_Step5_hours
, strat.TimeSpent_Step6_hours
, ord.TimeSpent_Step1_Net
, ord.TimeSpent_Step3_Net
, case when edd.CustomsIn is not null and edd.CustomsOut is not
 ↪  null then 'Yes' else 'No' end as [HasCustoms?]
, case when edd.CustomsIn is not null and edd.CustomsOut is not
 ↪  null then DATEDIFF(hour, edd.SentDate, edd.CustomsIn) else null
 ↪  end as TimeBeforeCustoms
, case when edd.CustomsIn is not null and edd.CustomsOut is not
 ↪  null then DATEDIFF(hour, edd.CustomsIn, edd.CustomsOut) else
 ↪  null end as TimeInCustoms
, case when edd.CustomsIn is not null and edd.CustomsOut is not
 ↪  null then DATEDIFF(hour, edd.CustomsOut, edd.ReceivedDate) else
 ↪  null end as TimeAfterCustoms
, case when edd.CustomsIn is not null and edd.CustomsOut is null
 ↪  then DATEDIFF(hour, edd.SentDate, edd.ReceivedDate) else null
 ↪  end as TimeInTransit
, CONVERT(decimal(8,2), strat.LeadTime_hours/24.0) as LeadTime_days
, edd.EDD_CheckOut
, case when edd.EDD_CheckOut = 'Too Early' then 1 else 0 end as
 ↪  TooEarly
```

```
, case when edd.EDD_CheckOut = 'Too Late' then 1 else 0 end as
 ↪  TooLate
, case when edd.[GoodDataQuality] = 'Yes' and edd.[OutlierSOS]=
 ↪  'No' and edd.[OutlierStep6] = 'No' then 1
    else 0 end as [DeliveryOutlier?]
into #AllDates
from [BI_DW].[dbo].FactOrdersLines ord
left join bixpl.[ANALYSTS].[dbo].[OPS_Strat_Times] strat on
 ↪  strat.BoutiqueOrder = ord.OrderCodeId
left join bixpl.[ANALYSTS].[dbo].[OPS_Del_KPI_Time] edd on
 ↪  ord.OrderCodeId = edd.OrderCodeID
where YEAR(ord.OrderDate_GMT) >= 2018

drop table if exists #Returns
select ord.OrderLineId
, ord.OrderSiteID
, ord.OrderCodeID
, case when ord.CancelNoStockDate is not null then 1
    when ord.OtherCancellationsDate is not null then 1
    when ord.CancelDate is not null then 1
    else 0 end as Cancelled
, case when ord.ReturnReason <> '-2' then 1
    else 0 end as Returned
, case when ord.ReturnReason <> '-2' then ord.ReturnReason
    else null end as ReturnReason
, case when ord.ReturnReason like 'Change%' or ord.ReturnReason
 ↪  like 'chang%' or ord.ReturnReason like '%cambiato%' or
 ↪  ord.ReturnReason like '%ideia%' then 'Changed My Mind'
    when ord.ReturnReason like '%problem%' or ord.ReturnReason like
     ↪  '%trop%' or ord.ReturnReason like '%ist zu%' or
     ↪  ord.ReturnReason like '%fit%' or ord.ReturnReason like
     ↪  '%too%' or ord.ReturnReason like '%tamanho%' then 'Fitting
     ↪  Problems'
    when ord.ReturnReason like 'beschrieb%' or ord.ReturnReason
     ↪  like '%acord%' or ord.ReturnReason like '%describe%' then
     ↪  'Item not as described'
    when ord.ReturnReason like '%sbagli%' or ord.ReturnReason like
     ↪  'Falsch%' or ord.ReturnReason like '%errad%' or
     ↪  ord.ReturnReason like 'Wrong%' then 'Wrong Item'
    when ord.ReturnReason like 'Defeit%' or ord.ReturnReason like
     ↪  'Défau%' or ord.ReturnReason like 'Difettat%' or
     ↪  ord.ReturnReason like 'Fault%' or ord.ReturnReason like
     ↪  '%fault%' or ord.ReturnReason like 'mangel%' then 'Faulty
     ↪  Item'
    when ord.ReturnReason like 'Quali%' then 'Quality Issues'
    when ord.ReturnReason = '-2' then null
```

```
    else 'Other' end as ReturnReasonDefault
, case when ord.ReturnReason <> '-2' then ord.ReturnReceivedDate
    else null end as ReturnReceivedDate
, case when ord.ReturnReason <> '-2' and
 ↪  ord.ReturnAcceptedByStoreDate is not null then
 ↪  ord.ReturnAcceptedByStoreDate
    when ord.ReturnReason <> '-2' and ord.ReturnRefusedByStoreDate
     ↪  is not null then ord.ReturnRefusedByStoreDate
    else null end as ReturnEvaluationDate
, case when ord.ReturnReason <> '-2' and
 ↪  ord.ReturnAcceptedByStoreDate is not null then 'Partner'
    when ord.ReturnReason <> '-2' and ord.ReturnRefusedByStoreDate
     ↪  is not null then 'FF'
    when ord.ReturnReason = '-2' then null
    else 'NoData' end as RefundByWho
, ord.RefundDate
into #Returns
from [BI_DW].[dbo].FactOrdersLines ord
where YEAR(ord.OrderDate_GMT) >= 2018

-------------------------------------------------------

drop table if exists [BI_ANALYTICS].[dbo].SCA_Scorecard
select
distinct o.OrderLineId
, o.TenantID
, o.OrderSiteID
, o.OrderCodeID
, o.OrderCode
, d.OrderDate_GMT
, a.Timezone
, a.OrderDate_PartnerTMZ
, a.CreatedHour_PartnerTMZ
, o.ProductID
, o.StoreKey
, o.LocalID
, o.StoreName
, o.SiteName
, o.Tier
, o.[Group]
, o.[Type]
, o.Office
, o.StoreRegion
, o.StoreCountryID
, o.StoreCountry
, o.StoreCity
```

```
, o.UserID
, o.[NewCustomer?]
, o.CustomerRegion
, o.CustomerCountryID
, o.CustomerCountry
, o.CustomerCity
, o.StoreCountry+'-'+o.CustomerCountry as ShipRoute
, o.DeliveryType
, o.[Value]
, case when a.BusinessType = 'Regular' then 'BaU'
    when a.BusinessType = 'FF Warehouse' then 'FxFF'
    else a.BusinessType end as BusinessType
, a.FxFF
, a.Regular
, a.FashionConcierge
, d.Year_Created
, d.Quarter_Created
, d.Month_Created
, d.Week_Created
, d.Year_NS
, d.Quarter_NS
, d.Month_NS
, d.Week_NS
, d.Year_Sent
, d.Quarter_Sent
, d.Month_Sent
, d.Week_Sent
, d.Year_Received
, d.Quarter_Received
, d.Month_Received
, d.Week_Received
, d.Year_Returned
, d.Quarter_Returned
, d.Month_Returned
, d.Week_Returned
, d.CancelDate
, d.CancelNoStockDate
, d.NS_Eval_Date
, o.Cancelled
, o.Delivered
, o.Returned
, a.HasDailyPickup
, case when a.AfterHoursOrder = 1 then 1
    else 0 end as AfterHoursOrder
, case when a.ReadyAfterPickUp = 1 then 1
    else 0 end as ReadyAfterPickUp
```

```
, k.HadNoStock
, k.IsItemSwapParent
, k.IsItemSwapChild
, k.SaA
, k.SaA_Decision
, k.FF_Fault
, k.NS_Net
, k.NS_Gross
, case when o.[NewCustomer?] = 1 and k.NS_Net = 1 then 1     else 0
 ↪  end as NewCust_NS_Net
, case when o.[NewCustomer?] = 1 and k.NS_Gross = 1 then 1
    else 0 end as NewCust_NS_Gross
, k.SoS_hours_Net
, k.SoS_days_Net
, k.SoS_Net_1d
, k.SoS_Net_2d
, k.SoS_hours
, k.SoS_days
, k.TT_hours
, k.TT_days
, k.LeadTime_hours
, k.LeadTime_days
, d.EDD_CheckOut
, d.[DeliveryOutlier?]
, k.[NoStock?]
, k.[TooEarly?]
, k.[TooLate?]
, k.[WrongItem?]
, k.[IsPOF?]
, k.[POF_Partner?]
, d.Step0_CreatedDate_GMT
, d.Step1_StockOK_GMT
, d.Step2_PaymentOK_GMT
, d.Step3_PackagingOK_GMT
, d.Step4_ReadyToSend_GMT
, d.Step5_OrderPickup_GMT
, d.Step6_Received_GMT
, d.TimeSpent_Step1_hours
, d.TimeSpent_Step2_hours
, d.TimeSpent_Step3_hours
, d.TimeSpent_Step4_hours
, d.TimeSpent_Step5_hours
, d.TimeSpent_Step6_hours
, d.TimeSpent_Step1_Net
, d.TimeSpent_Step3_Net
, d.[HasCustoms?]
```

```
, d.TimeBeforeCustoms
, d.TimeInCustoms
, d.TimeAfterCustoms
, d.TimeInTransit
, r.ReturnReason
, case when r.ReturnReasonDefault = 'Wrong Item' then 1
    else 0 end as WrongItem
, r.ReturnReasonDefault
, r.ReturnReceivedDate
, r.ReturnEvaluationDate
, r.RefundByWho
, r.RefundDate
into [BI_ANALYTICS].[dbo].SCA_Scorecard
from #Overview o
LEFT join #AddInfoStore a on o.OrderLineID = a.OrderLineId
LEFT join #KPIs k on o.OrderLineId = k.OrderLineId
LEFT join #AllDates d on o.OrderLineID = d.OrderLineId
LEFT join #Returns r on o.OrderLineId = r.OrderLineId
order by OrderLineID
```

C.2 BI_ANLYTICS.dbo.SCA_POF

This table is also constructed based on several temporary subtables, which are created and deleted each time the query is run. Only the data contained in the final table is presented and briefly explained.

Some of the contained information coincides with information in table *SCORECARD* - these common columns serve as ways to join the different tables in Tableau software.

- **OrderDate_GMT** - Order's creation date;
- **Year_POF** - Self Explanatory;
- **Quarter_POF** - Self Explanatory;
- **Month_POF** - Self Explanatory;
- **Week_POF** - Self Explanatory;
- **OrderSiteID** - Identification of a Portal Order;
- **OrderCodeID** - Identification of a Boutique Order;
- **SiteName** - Self explanatory;
- **Tier** - Self Explanatory;
- **Group** - Self Explanatory;
- **Type** - Information whether partner is a boutique or a brand;
- **Office** - Information of which FF office supports the partner;
- **BusiType** - Information whether shipment is made through 'FxFF', 'BaU' or 'Fashion Concierge';

- **UserID** - Client's unique identifier;
- **NewCustomer?** - Binary description whether it is the customer's first purchase;
- **StoreRegion** - Identification of the region where the partner is located;
- **StoreCountry** - Identification of the country where the store is located;
- **CustomerRegion** - Identification of the shipping destination region;
- **CustomerCountry** - Identification of the shipping destination country;
- **DeliveryType** - Information whether shipment is 'Crossborder', 'Domestic' or 'IntraEu';
- **NoStock?** - Binary information on whether a Boutique Order had at most one No Stock occurrence;
- **TooEarly?** - Binary information on whether a Boutique Order was delivered too early;
- **TooLate?** - Binary information on whether a Boutique Order was delivered too late;
- **ReturnWI** - Binary information on whether at most one product within a Boutique Order was returned due to a wrong item;
- **POF** - Binary information on whether a Boutique Order is considered a perfect order;
- **POF_PartnerView** - Binary information on whether a Boutique Order is considered a perfect order, from a partner's perspective;
- **NoPOFReason** - Information on the Boutique Order's reason for not having been perfect.

SQL query originating table BI_ANLYTICS.DBO.POF

```
-------------------- Set Monday as starting week day
SET DATEFIRST 1
drop table if exists #OrderLines
select
fol.OrderDate_GMT
, fol.ReceivedDate_GMT
, fol.CancelDate
, fol.OrderLineId
, fol.SiteId
, fol.OrderCodeID
, fol.ProductID
, case when fol.HadNoStock ='yes' then 1 else 0 end as HadNoStock
, case when fol.CancelNoStockDate is not null then 1 else 0 end as
 ↪  CancelledNoStock
, case when fol.IsItemSwapParent = 'yes' then 1 else 0 end as
 ↪  IsItemSwapParent
, case when fol.IsItemSwapParent = 'no' then 1 else 0 end as
 ↪  IsItemSwapChild
, case when fol.CancelDate is not null and fol.CancelNoStockDate is
 ↪  null then 1 else 0 end as CancelledByCustomer
into #OrderLines
from BI_DW.dbo.factorderslines fol
```

```
where YEAR(ReceivedDate_GMT) >= 2018 or YEAR(CancelDate) >= 2018
    and fol.TenantId = 10000

drop table if exists #OrderLines2
select
OrderDate_GMT
, ReceivedDate_GMT
, CancelDate
, OrderLineId
, OrderCodeID
, ProductID
, HadNoStock
, IsItemSwapParent
, IsItemSwapChild
, CancelledNoStock
, CancelledByCustomer
, case when CancelledByCustomer = 1 then 0
    when IsItemSwapParent = 1 then 0
    else 1 end as POF_Eligible
into #OrderLines2
from #OrderLines
where YEAR(ReceivedDate_GMT) >= 2018 or YEAR(CancelDate) >= 2018

drop table if exists #OrderLines3
select
OrderDate_GMT
, OrderLineId
, OrderCodeID
, ProductID
, HadNoStock
, IsItemSwapParent
, IsItemSwapChild
, CancelledNoStock
, CancelledByCustomer
, POF_Eligible
into #OrderLines3
from #OrderLines2
where Year(ReceivedDate_GMT) >= 2018 or YEAR(CancelDate) >= 2018
    and POF_Eligible = 1

------- Group by number of occurrences within an OrderCodeID

drop table if exists #OrderCodeIDs
select a.OrderDate_GMT
, max(fol.ReceivedDate_GMT) as ReceivedDate
, max(fol.CancelDate) as CancelDate
```

```
, fol.OrderSiteId
, a.OrderCodeID
, store.SiteName
, suc.Tier as Tier
, suc.[Group]
, suc.[Type]
, suc.Office
,(select ds.businesstype from [BI_DW].[dbo].dimstore ds where
 ↪ ds.localid=fol.storekey and ds.rowexcludedate is null) as
 ↪ busitype
, fol.UserID
, case when a.OrderDate_GMT = u.FirstPurchaseDate then 1 else 0 end
 ↪ as [NewCustomer?]
, geostore.RegionCustomerFF as StoreRegion
, geostore.Country as StoreCountry
, geo.RegionCustomerFF as CustomerRegion
, geo.Country as CustomerCountry
, case when geostore.Country = geo.Country then 'Domestic'
    when geostore.ZonaEuro = 'Yes' and geo.ZonaEuro = 'Yes' then
     ↪ 'Intra-EU'
    else 'Crossborder' end as DeliveryType
, count(a.OrderCodeId) as NrProducts
, sum(a.POF_Eligible) as POF_Eligible
, a.CancelledNoStock as [NoStock?]
, case when edd.[EDD_Checkout] = 'Too early' then 1 else 0 end as
 ↪ [TooEarly?]
, case when edd.[EDD_Checkout] = 'Too late'  then 1 else 0 end as
 ↪ [TooLate?]
, case when ret.IsWrongItem = 'No' then 0 else 1 end as
 ↪ ReturnWrongItem
, case when edd.[EDD_Checkout] = 'Bananas' or edd.[EDD_Checkout] =
 ↪ 'N/A' then 1 else 0 end as PoorDataQuality
into #OrderCodeIDs
from #OrderLines3 a
left join [BI_DW].[dbo].factorderslines fol on a.OrderLineId =
 ↪ fol.OrderLineId
left join bixpl.[ANALYSTS].[dbo].[OPS_Del_KPI_Time] edd on
 ↪ fol.OrderCodeId = edd.OrderCodeID
left join [BI_DW].[dbo].[DimStore] store on fol.SK_Store =
 ↪ store.SK_Store
left join [BI_DW].[dbo].[DimReturnReason] ret on
 ↪ fol.SK_ReturnReason = ret.SK_ReturnReason
left join [BI_DW].[dbo].DimUser u on fol.SK_User = u.SK_User
inner join [BI_DW].[dbo].DimGeography geo on fol.SK_GeographyBill =
 ↪ geo.SK_Geography
```

```
inner join [BI_DW].[dbo].DimGeography geostore on
 ↪ geostore.SK_Geography = store.SK_StoreAddress
inner join [BI_ANALYTICS].[dbo].Success_Segments suc on
 ↪ suc.StoreKey = store.StoreKey
where datepart(YEAR,ReceivedDate_GMT) >= 2018 or
 ↪ datepart(year,CancelDate) >= 2018
    and fol.TenantId = 10000
group by a.OrderDate_GMT, fol.ReceivedDate_GMT, fol.CancelDate,
 ↪ fol.OrderSiteId, a.OrderCodeID, fol.Orderlineid,
 ↪ store.SiteName, store.LocalID, a.hadnostock,
 ↪ a.CancelledNoStock, a.IsItemSwapParent, edd.[EDD_Checkout],
 ↪ ret.IsWrongItem, suc.Tier, suc.[Group], suc.[Type], suc.Office,
 ↪ geostore.RegionCustomerFF, geostore.Country, geostore.ZonaEuro,
 ↪ geo.RegionCustomerFF, geo.Country, geo.ZonaEuro, fol.UserID,
 ↪ u.FirstPurchaseDate, fol.storekey
order by a.OrderDate_GMT

drop table if exists #OrderCodeIDs2
select
OrderDate_GMT
, OrderSiteID
, OrderCodeID
, SiteName
, Tier
, [Group]
, [Type]
, Office
, case when BusiType = 'Regular' then 'BaU'
    when BusiType = 'FF Warehouse' then 'FxFF' else busitype end as
     ↪ BusiType
, StoreRegion
, StoreCountry
, UserID
, [NewCustomer?]
, CustomerRegion
, CustomerCountry
, DeliveryType
, max(case when DATEPART(year, ReceivedDate) is not null
    then DATEPART(year, ReceivedDate)
    else datepart(year, Canceldate) end) as Year_POF
, max(case when DATEPART(quarter, ReceivedDate) is not null
    then DATEPART(quarter, ReceivedDate)
        else datepart(quarter, Canceldate) end) as Quarter_POF
, max(case when DATEPART(month, ReceivedDate) is not null
        then DATEPART(month, ReceivedDate)
        else datepart(month, Canceldate) end) as Month_POF
```

```
, max(case when DATEPART(week, ReceivedDate) is not null
        then DATEPART(week, ReceivedDate)
        else datepart(week, Canceldate) end) as Week_POF
, SUM(NrProducts) as NrProducts
, SUM(POF_Eligible) as POF_Eligible
, case when SUM([NoStock?]) > 0 then 1 else 0 end as [NoStock?]
, case when [TooEarly?] = 1 then 1 else 0 end as [TooEarly?]
, case when [TooLate?] = 1 then 1 else 0 end as [TooLate?]
, case when SUM(ReturnWrongItem) > 0 then 1 else 0 end as ReturnWI
into #OrderCodeIDs2
from #OrderCodeIDs
group by OrderDate_GMT, OrderCodeId, OrderSiteID, SiteName, Tier,
 ↪   [Group], [Type], Office, StoreRegion, StoreCountry,
 ↪   CustomerRegion, CustomerCountry, DeliveryType, UserID,
 ↪   [NewCustomer?], [TooEarly?], [TooLate?], BusiType

------- Group all relevant data of a particular OrderCodeID

drop table if exists [BI_ANALYTICS].[dbo].SCA_JF_POF_JP
select OrderDate_GMT
, Year_POF
, Quarter_POF
, Month_POF
, Week_POF
, OrderSiteID
, OrderCodeID
, SiteName
, Tier
, [Group]
, [Type]
, Office
, BusiType
, UserID
, [NewCustomer?]
, StoreRegion
, StoreCountry
, CustomerRegion
, CustomerCountry
, DeliveryType
, [NoStock?]
, [TooEarly?]
, [TooLate?]
, ReturnWI
, case when [NoStock?] = 0 and [TooEarly?] = 0 and [TooLate?] = 0
 ↪   and ReturnWI = 0 then 'Yes'
    else 'No' end as POF
```

```
, case when [NoStock?] = 0 and [TooLate?] = 0 and ReturnWI = 0 then
 ↪  'Yes'
    else 'No' end as POF_PartnerView
, case when [NoStock?] = 1 then 'No Stock'
    when [TooEarly?] = 1 then 'Too Early'
    when [TooLate?] = 1 then 'Too Late'
    when ReturnWI = 1 then 'Return WI'
    else 'POF' end as NoPOFReason
into [BI_ANALYTICS].[dbo].SCA_JF_POF_JP
from #OrderCodeIDs2
where Year_POF >= 2018
order by OrderDate_GMT
```

C.3 BI_ANLYTICS.dbo.SCA_NrRD

The same method is used to present the SQL table containing information regarding ruined days, and the same considerations also apply for this table.

- **Year_RD** - Self Explanatory;
- **Quarter_RD** - Self Explanatory;
- **Month_RD** - Self Explanatory;
- **Week_RD** - Self Explanatory;
- **Day_RD** - Self Explanatory;
- **SK_User** - Unique user identifier, key to link tables in Farfetch's database;
- **OrderLineID** - Identification of a Product Order;
- **OrderSiteID** - Identification of a Portal Order;
- **OrderCodeID** - Identification of a Boutique Order;
- **StoreID** - Unique Site Identifier (Alias to *LocalID*);
- **SiteName** - Self explanatory;
- **StoreRegion** - Identification of the region where the partner is located;
- **StoreCountryID** - Unique identifier of the partner's country;
- **StoreCountry** - Identification of the country where the store is located;
- **Tier** - Self Explanatory;
- **Group** - Self Explanatory;
- **Type** - Information whether partner is a boutique or a brand;
- **Office** - Information of which FF office supports the partner;
- **BusinessType** - Information whether shipment is made through 'FxFF', 'BaU' or 'Fashion Concierge';

- **FxFF** - Binary variable;
- **CustomerRegion** - Identification of the shipping destination region;
- **CustomerCountryID** - Unique identifier of the shipping country;
- **CustomerCountry** - Identification of the shipping destination country;
- **DeliveryType** - Information whether order shipment is 'Crossborder', 'Domestic' or 'IntraEu';
- **UserID** - Client's unique identifier;
- **NewCustomer?** - Binary description whether it is the customer's first purchase;
- **RuinedClient** - Binary information on whether a client is considered to have been ruined;
- **NrRuinedDays** - Display of the number of ruined days per Product Order.

SQL query originating table BI_ANLYTICS.DBO.NrRD

```
-------------------- Set Monday as starting week day
SET DATEFIRST 1
drop table if exists #AllOrders
select
fol.OrderDate_GMT
, fol.CancelDate
, fol.ReceivedDate_GMT
, fol.SK_User
, fol.OrderLineId
, fol.OrderSiteId
, fol.OrderCodeID
, store.LocalID as StoreID
, store.StoreName
, store.SiteName
, geostore.RegionCustomerFF as StoreRegion
, geostore.PaisID as StoreCountryID
, geostore.Country as StoreCountry
, geostore.City as StoreCity
, suc.Tier as Tier
, suc.[Group]
, suc.[Type]
, suc.Office
, store1.BusinessType
, case when store1.BusinessType = 'FF Warehouse' then 1
    else 0 end as FxFF
, geo.RegionCustomerFF as CustomerRegion
, geo.PaisID as CustomerCountryID
, geo.Country as CustomerCountry
, case when geostore.Country = geo.Country then 'Domestic'
```

```
    when geostore.ZonaEuro = 'Yes' and geo.ZonaEuro = 'Yes' then
     ↪ 'Intra-EU'
    else 'Crossborder' end as DeliveryType
, fol.UserID
, case when fol.OrderDate_GMT = u.FirstPurchaseDate then 1
    else 0 end as [NewCustomer?]
, fol.ProductID
, case when fol.CancelDate is not null and fol.CancelNoStockDate is
 ↪ null then 1
    else 0 end as CancelledByCustomer
, case when fol.CancelNoStockDate is not null then 1
    else 0 end as CancelledByNoStock
, case when fol.ReceivedDate is not null then 1
   else 0 end as Received
, case when fol.ReturnReason <> '-2' then 1
   else 0 end as Returned
, case when fol.ReturnReason <> '-2' then fol.ReturnReason
   else null end as ReturnReason
, case when fol.ReturnReason <> '-2' then fol.RefundDate
   else null end as RefundDate
into #AllOrders
from [BI_DW].[dbo].FactOrdersLines fol
inner join [BI_DW].[dbo].DimStore store on
 ↪ fol.sk_store=store.SK_Store
inner join [BI_DW].[dbo].DimStore store1 on
 ↪ fol.StoreKey=store1.LocalID
inner join [BI_DW].[dbo].DimGeography geo on fol.SK_GeographyBill =
 ↪ geo.SK_Geography
inner join [BI_DW].[dbo].DimGeography geostore on
 ↪ geostore.SK_Geography = store.SK_StoreAddress
inner join [BI_ANALYTICS].[dbo].Success_Segments suc on
 ↪ suc.StoreKey = store.StoreKey
left join [BI_DW].[dbo].DimUser u on fol.SK_User = u.SK_User
where YEAR(OrderDate_GMT) >= 2018
    and store1.RowExcludeDate is null

drop table if exists #RD_Calculation
select
a.Orderdate_GMT
, a.CancelDate
, a.ReceivedDate_GMT
, a.SK_User
, a.OrderLineId
, a.OrderSiteId
, a.OrderCodeID
, a.StoreID
```

```
, a.SiteName
, a.StoreRegion
, a.StoreCountryID
, a.StoreCountry
, a.Tier
, a.[Group]
, a.[Type]
, a.Office
, case when a.BusinessType = 'Regular' then 'BaU'
    when a.BusinessType = 'FF Warehouse' then 'FxFF'
    else a.BusinessType end as BusinessType
, a.FxFF
, a.CustomerRegion
, a.CustomerCountryID
, a.CustomerCountry
, a.DeliveryType
, a.USerID
, a.[NewCustomer?]
, a.ProductID
, a.CancelledByCustomer
, a.CancelledByNoStock
, a.Received
, a.Returned
, a.ReturnReason
, case when a.Returned = 1 and a.ReturnReason like '%sbagli%' or
 ↪  a.ReturnReason like 'Falsch%' or a.ReturnReason like '%errad%'
 ↪  or a.ReturnReason like 'Wrong%' then 1
    else 0 end as Return_FF_Fault
, case when edd.EDD_CheckOut = 'Too Early' or edd.EDD_CheckOut =
 ↪  'Too Late' then 1
    else 0 end as NotInTime
, case when edd.EDD_CheckOut = 'Too Early' then        1
    when edd.EDD_CheckOut = 'Too Late' then ((edd.SosNet +
      ↪  edd.Step6Net) * 24 - edd.EDD_CheckOut_Max)/24.0
    else 0 end as NotInTime_Days
, case when edd.EDD_CheckOut = 'Too Early' then CEILING(1)
    when edd.EDD_CheckOut = 'Too Late' then CEILING(((edd.SosNet +
      ↪  edd.Step6Net) * 24 - edd.EDD_CheckOut_Max)/24.0)
    else 0 end as NotInTime_Days_Rounded
into #RD_Calculation
from #AllOrders a
left join bixpl.[ANALYSTS].[dbo].[OPS_Del_KPI_Time] edd on
 ↪  a.OrderCodeId = edd.OrderCodeID

drop table if exists #Auxiliar
select
```

```
r.ReceivedDate_GMT
, r.CancelDate ,
case when r.ReceivedDate_GMT is not null
    then DATEPART(year, r.ReceivedDate_GMT)
    else datepart(year, r.Canceldate) end as Year_RD
, case when DATEPART(quarter, r.ReceivedDate_GMT) is not null
    then DATEPART(quarter, r.ReceivedDate_GMT)
    else datepart(quarter, r.Canceldate) end as Quarter_RD
, case when DATEPART(month, r.ReceivedDate_GMT) is not null
    then DATEPART(month, r.ReceivedDate_GMT)
    else datepart(month, r.Canceldate) end as Month_RD
, case when DATEPART(week, r.ReceivedDate_GMT) is not null
    then DATEPART(week, r.ReceivedDate_GMT)
    else datepart(week, r.Canceldate) end as Week_RD
, case when DATEPART(day, r.ReceivedDate_GMT) is not null
    then DATEPART(day, r.ReceivedDate_GMT)
    else datepart(day, r.Canceldate) end as Day_RD
, r.SK_User
, r.OrderLineID
, r.OrderCodeId
, r.OrderSiteId
, r.StoreID
, r.SiteName
, r.StoreRegion
, r.StoreCountryID
, r.StoreCountry
, r.Tier
, r.[Group]
, r.[Type]
, r.Office
, r.BusinessType
, r.FxFF
, r.CustomerRegion
, r.CustomerCountryID
, r.CustomerCountry
, r.DeliveryType
, r.UserID
, r.[NewCustomer?]
, case when r.CancelledByNoStock = 1 or r.Return_FF_Fault = 1 or
 ↪ r.NotInTime = 1
    then sum(r.CancelledByNoStock + r.Return_FF_Fault +
     ↪ NotInTime_Days_Rounded)
    else 0 end as NrRuinedDays
into #Auxiliar
from #RD_Calculation r
```

```
group by r.ReceivedDate_GMT, r.CancelDate, r.SK_User,
 ↪  r.OrderLineID, r.OrderCodeId, r.OrderSiteId,
 ↪  r.CancelledByNoStock, r.Return_FF_Fault, r.NotInTime, r.FxFF,
 ↪  r.BusinessType, r.StoreID , r.SiteName, r.StoreRegion,
 ↪  r.StoreCountryID, r.StoreCountry, r.CustomerRegion,
 ↪  r.CustomerCountryID, r.CustomerCountry, r.DeliveryType, r.Tier,
 ↪  r.[Group], r.[Type], r.Office, r.UserID, r.[NewCustomer?]

drop table if exists [BI_ANALYTICS].[dbo].SCA_JF_RD_Orderlines
select
Year_RD
, Quarter_RD
, Month_RD
, Week_RD
, Day_RD
, SK_User
, OrderLineID
, OrderSiteId
, OrderCodeId
, StoreID
, SiteName
, StoreRegion
, StoreCountryID
, StoreCountry
, Tier
, [Group]
, [Type]
, Office
, BusinessType
, FxFF
, CustomerRegion
, CustomerCountryID
, CustomerCountry
, DeliveryType
, USerID
, [NewCustomer?]
, case when NrRuinedDays > 0 then 1
    else 0 end as RuinedClient
, NrRuinedDays
into [BI_ANALYTICS].[dbo].SCA_JF_RD_Orderlines
from #Auxiliar
where Year_RD >= 2018
order by Year_RD, Month_RD, Week_RD, Day_RD
```

C.4 SQL Procedures

A stored procedure in SQL has the form presented next, where the 'original' SQL code is simply added in place of [...].

```
USE [BI_ANALYTICS]
GO
SET ANSI_NULLS ON
GO
SET QUOTED_IDENTIFIER ON
GO
CREATE PROCEDURE [dbo].[SCA_JF_RefreshScorecard]
AS
BEGIN
[...]
SET NOCOUNT ON;
END
GO
```

Appendix D

Calculations in Tableau

As explained in Chapter 4, Tableau allows a great variety of calculations in a very simple way. Two examples of in Tableau calculated metrics - so called Calculated Field - are shown in Figure D.1.

Figure D.1: Example of metrics' calculation in Tableau

Figure D.1 exemplifies the simplicity the use of binary columns in the feeding tables provides to calculate the KPIs, in this case the NS Net and the SoS < 2d Net.

About 80 such Calculated Fields have been created in Tableau (one, at least, for each weekly, monthly or quarterly metric) - however, due to lack of space, their development is not presented.

The comparison of dimensions - [Week_NS] and [Year_NS] - with the created parameters - [Week] and [Year] - is also illustrated in this example.

An example of one of the created parameters is shown in Figure D.2.

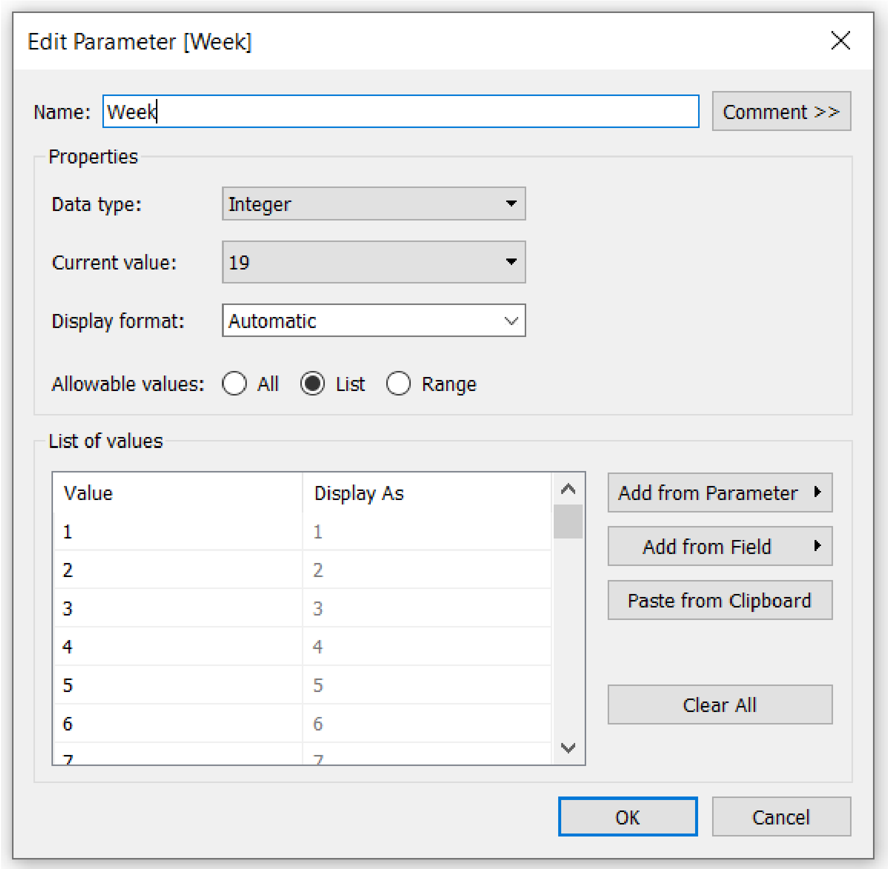

Figure D.2: Example of the construction of a parameter in Tableau

Appendix E

Python Code to get partners' time zones and offsets towards UTC

The code used to get the time zones and respective offset towards UTC is presented in this section. API Mapbox was used to code in Python language.

The final table obtained with this code was exported to an Excel file. This was afterwards imported to Farfetch's database (with the help of SQL Server 2017 Importer and Exporter), originating table BI_ANLYTICS.DBO.SCA_Timezones.

```
import pyodbc
import pandas as pd
import numpy as np
import scipy.stats as ss
import matplotlib.pyplot as plt
from scipy.optimize import minimize
import statsmodels.api as sm
import copy
import seaborn as sns
import patsy
import pylab
from scipy import stats
import xlsxwriter
from sklearn import preprocessing
from pydoc import help
from scipy.stats.stats import pearsonr
from pandas import ExcelWriter
from pandas import ExcelFile
import urllib
import os
os.getcwd()
os.chdir("C:\\Users\\joaolopes.ferreira\\Desktop")
import pytz
import xlwt
import datetime
```

```
from time import gmtime,strftime
from datetime import timedelta as td, datetime
from opencage.geocoder import OpenCageGeocode
from timezonefinder import TimezoneFinder
from mapbox import Geocoder
geocoder = geocoder =
 ↪  Geocoder(access_token="pk.eyJ1Ijoi[...]Hh6rw")

#STORES RoW
server = 'bidw.farfetch.net'
db = 'BI_ANALYTICS'
tb = '[dbo].SCA_Scorecard'
conn=pyodbc.connect('DSN=bidw')

sql1 = "select distinct store.LocalID, store.StoreName,
 ↪  store.SiteName, geo.Continent, geo.Country, geo.CountryCode,
 ↪  geo.[State], geo.City \
from [BI_DW].[dbo].DimStore store \
inner join [BI_DW].[dbo].DimGeography geo on geo.SK_Geography =
 ↪  store.SK_ShipAddress \
where StoreName is not null and StoreName <> 'N/D' and geo.Country
 ↪  <> 'United States' and geo.City <> ' ' \
order by StoreName"
data1 = pd.read_sql(sql1, conn)
df_row = pd.DataFrame(data1)
print(df_row)

df_row['City'] = df_row['City'].replace(['Ichikawashi'],['Ichikawa
 ↪  city'])
df_row['City'] = df_row['City'].str.title()

#Coordinates for each row
data2 = []
i=0
for index, row in df_row.iterrows():
    CityName=(row['City'])
    CountryName =(row['Country'])
    Query = str(CityName)+','+str(CountryName)
    responseStore = geocoder.forward(Query)
    CityCoords=[]
    if responseStore.geojson()['features']:
        firstaux = responseStore.geojson()['features'][0]
        CityCoords = [float(coord) for coord in
         ↪  firstaux['geometry']['coordinates']]
        print(CityCoords)
        CityCoords[0], CityCoords[1]=CityCoords[1], CityCoords[0]
```

```
    else:
        CityCoords=[]
    i=i+1
    print(i)
    data2.append([CountryName,CityName,CityCoords])

dfcitycoords = pd.DataFrame(data2)
dfcitycoords=dfcitycoords.rename(columns={0:'CountryName',
 ↪  1:'CityName', 2:'CityCoords'})
print(dfcitycoords)

df_total = pd.concat([df_row, dfcitycoords], axis=1)
df_total = df_total.drop(['CountryName', 'CityName'], axis = 1)
df_total[['Latitude',
 ↪  'Longitude']]=pd.DataFrame(df_total.CityCoords.values.tolist())

print(df_total)

#TMZ for each row
tf = TimezoneFinder()
tf = TimezoneFinder(in_memory=True)

data3 = []
i=0
for index, row in df_total.iterrows():
    latitude=(row['Latitude'])
    longitude=(row['Longitude'])
    tmz = tf.certain_timezone_at(lng=longitude, lat=latitude)
    i=i+1
    data3.append([latitude, longitude, tmz])
dftmz = pd.DataFrame(data3)
dftmz=dftmz.rename(columns={0: 'Latitude', 1: 'Longitude', 2:
 ↪  'Timezone'})
print(dftmz)

df_tmz = pd.concat([df_total, dftmz], axis=1)
df_tmz = df_tmz.drop(['Latitude', 'Longitude'], axis = 1)
df_tmz['State'] = 'N/D'
print(df_tmz)

#STORES USA
server = 'bidw.farfetch.net'
db = 'BI_ANALYTICS'
tb = '[dbo].SCA_Scorecard'
conn=pyodbc.connect('DSN=bidw')
```

```
sql12 = "select distinct store.localid, store.StoreName,
 ↪ store.SiteName, geo.Continent, geo.Country, geo.CountryCode,
 ↪ geo.[State] as [State] \
, CASE WHEN geo.[State] = 'Alaska' then 'AK' \
WHEN geo.[State] = 'Alabama' then 'AL' \
WHEN geo.[State] = 'Arkansas' then 'AR' \
WHEN geo.[State] = 'American Samoa' then 'AS' \
WHEN geo.[State] = 'Arizona' then 'AZ' \
WHEN geo.[State] = 'California' then 'CA' \
WHEN geo.[State] = 'Colorado' then 'CO' \
WHEN geo.[State] = 'Connecticut' then 'CT' \
WHEN geo.[State] = 'District Of Columbia' then 'DC' \
WHEN geo.[State] = 'Delaware' then 'DE' \
WHEN geo.[State] = 'Florida' then 'FL' \
WHEN geo.[State] = 'Federated States of Micronesia' then 'FM' \
WHEN geo.[State] = 'Georgia' then 'GA' \
WHEN geo.[State] = 'Guam ' then'GU'  \
WHEN geo.[State] = 'Hawaii' then'HI'  \
WHEN geo.[State] = 'Iowa' then'IA'   \
WHEN geo.[State] = 'Idaho' then'ID'  \
WHEN geo.[State] = 'Illinois' then'IL'  \
WHEN geo.[State] = 'Indiana' then'IN'   \
WHEN geo.[State] = 'Kansas' then'KS'   \
WHEN geo.[State] = 'Kentucky' then'KY'  \
WHEN geo.[State] = 'Louisiana' then'LA'  \
WHEN geo.[State] = 'Massachusetts' then'MA'  \
WHEN geo.[State] = 'Maryland' then'MD'   \
WHEN geo.[State] = 'Maine' then'ME'  \
WHEN geo.[State] = 'Marshall Islands' then'MH'  \
WHEN geo.[State] = 'Michigan' then'MI'  \
WHEN geo.[State] = 'Minnesota' then'MN'   \
WHEN geo.[State] = 'Missouri' then'MO'    \
WHEN geo.[State] = 'Northern Mariana Islands' then'MP'  \
WHEN geo.[State] = 'Mississippi' then'MS'  \
WHEN geo.[State] = 'Montana' then'MT'  \
WHEN geo.[State] = 'North Carolina' then'NC'  \
WHEN geo.[State] = 'North Dakota' then'ND'  \
WHEN geo.[State] = 'Nebraska' then'NE'  \
WHEN geo.[State] = 'New Hampshire' then'NH'  \
WHEN geo.[State] = 'New Jersey' then'NJ'  \
WHEN geo.[State] = 'New Mexico' then'NM'  \
WHEN geo.[State] = 'Nevada' then'NV'  \
WHEN geo.[State] = 'New York' then'NY'  \
WHEN geo.[State] = 'Ohio' then 'OH'  \
WHEN geo.[State] = 'Oklahoma' then 'OK'  \
WHEN geo.[State] = 'Oregon' then 'OR'  \
```

```
WHEN geo.[State] = 'Pennsylvania' then 'PA'  \
WHEN geo.[State] = 'Puerto Rico' then 'PR'      \
WHEN geo.[State] = 'Rhode Island' then 'RI'   \
WHEN geo.[State] = 'South Carolina' then 'SC'  \
WHEN geo.[State] = 'South Dakota' then 'SD'   \
WHEN geo.[State] = 'Tennessee' then 'TN'   \
WHEN geo.[State] = 'Texas' then 'TX'   \
WHEN geo.[State] = 'Utah' then 'UT'   \
WHEN geo.[State] = 'Virginia' then 'VA'  \
WHEN geo.[State] = 'Virgin Islands' then 'VI'  \
WHEN geo.[State] = 'Vermont' then 'VT'   \
WHEN geo.[State] = 'Washington' then 'WA'   \
WHEN geo.[State] = 'Wisconsin' then 'WI'    \
WHEN geo.[State] = 'West Virginia' then 'WV'    \
WHEN geo.[State] = 'Wyoming' then'WY'  \
WHEN geo.[State] = 'NJ' then'NJ'  \
WHEN geo.[State] = 'NC' then'NC'  \
WHEN geo.[State] = 'CA' then'CA'  \
WHEN geo.[State] = 'Tn' then'TN'  \
WHEN geo.[State] = 'Oklahoma City' THEN 'OK' ELSE '' END as
 ↪ StateInitials, geo.city as City  \
from [bi_dw].[dbo].DimStore store \
inner join [BI_DW].[dbo].DimGeography geo on geo.SK_Geography =
 ↪ store.SK_ShipAddress  \
where Country = 'United States'"
data12 = pd.read_sql(sql12, conn)
df_us = pd.DataFrame(data12)
print(df_us)

#Coordinates for each row
data12 = []
i=0
for index, row in df_us.iterrows():
    CityName=(row['City'])
    StateName =(row['StateInitials'])
    Query = str(CityName)+','+str(StateName)
    responseStore = geocoder.forward(Query, country=['us'])
    CityCoords=[]
    if responseStore.geojson()['features']:
        firstaux = responseStore.geojson()['features'][0]
        CityCoords = [float(coord) for coord in
         ↪ firstaux['geometry']['coordinates']]
        print(CityCoords)
        CityCoords[0], CityCoords[1]=CityCoords[1], CityCoords[0]
    else:
        CityCoords=[]
```

```
    i=i+1
    print(i)
    data12.append([StateName,CityName,CityCoords])

dfcitycoords_us = pd.DataFrame(data12)
dfcitycoords_us=dfcitycoords_us.rename(columns={0:'State',
 ↪  1:'CityName', 2:'CityCoords'})
print(dfcitycoords_us)

df_total_us = pd.concat([df_us, dfcitycoords_us], axis=1)
df_total_us = df_total_us.drop(['State', 'CityName'], axis = 1)
df_total_us['City'] = df_total_us['City'].str.title()
df_total_us[['Latitude',
 ↪  'Longitude']]=pd.DataFrame(df_total_us.CityCoords.values.tolist())

print(df_total_us)

#TMZ for each row
tf = TimezoneFinder()
tf = TimezoneFinder(in_memory=True)

#latitude = 51.8333
#longitude = 0.5833
#tmz = tf.timezone_at(lng=longitude, lat=latitude)
#print(tmz)

data13 = []
i=0
for index, row in df_total_us.iterrows():
    latitude=(row['Latitude'])
    longitude=(row['Longitude'])
    tmz = tf.certain_timezone_at(lng=longitude, lat=latitude)
    i=i+1
    data13.append([latitude, longitude, tmz])
dftmz_us = pd.DataFrame(data13)
dftmz_us=dftmz_us.rename(columns={0: 'Latitude', 1: 'Longitude', 2:
 ↪  'Timezone'})
print(dftmz_us)

df_tmz_us = pd.concat([df_total_us, dftmz_us], axis=1)
df_tmz_us = df_tmz_us.drop(['Latitude', 'Longitude'], axis = 1)
df_tmz_us = df_tmz_us.rename(index=str, columns={"StateInitials":
 ↪  "State", "localid": "LocalID"})
print(df_tmz_us)

# Append both dataframes
```

```
df = df_tmz.append(df_tmz_us, ignore_index = True)
print(df)

tmz_calc=0.0
tmz_ds_calc=0.0
data5= []
i=0
for index, row in df.iterrows():
    tmz_name=(row['Timezone'])
    tmz =
     ↪ pytz.timezone(tmz_name).localize(datetime(2011,1,1)).strftime('%z')
     ↪ #Normal
    tmz_ds =
     ↪ pytz.timezone(tmz_name).localize(datetime(2011,8,1)).strftime('%z')
     ↪ #DaylightSavingTime
    if (round((float(tmz)/100),2)%1)==0:
        tmz_calc = round((float(tmz)/100),2)
        tmz_ds_calc = round((float(tmz_ds)/100),2)
    else:
        tmz_calc = round((float(tmz)/100),2)+0.2
        tmz_ds_calc = round((float(tmz)/100),2)+0.2
    i=i+1
    data5.append([tmz_name, tmz, tmz_ds, tmz_calc,tmz_ds_calc])
df_final = pd.DataFrame(data5)
df_final=df_final.rename(columns={0: 'TMZ_Name', 1: 'Offset', 2:
 ↪ 'DST_Offset', 3:'Offset_float', 4:'DST_Offset_float'})
print(df_final)

df_finalx = pd.concat([df, df_final], axis=1)
df_finalx = df_finalx.drop(['TMZ_Name'], axis = 1)
print(df_finalx)

#Create Excel file with multiple Sheets
writer = pd.ExcelWriter('Timezones.xlsx', engine = 'xlsxwriter')
df_tmz.to_excel(writer, sheet_name = 'RoW')
df_tmz_us.to_excel(writer, sheet_name = 'US')
df.to_excel(writer, sheet_name = 'Total')
df_finalx.to_excel(writer, sheet_name = 'SCA_JF_Timezones')
writer.save()
```

Appendix F

Python Code to identify benchmarks for number of orders in the pipeline

This Appendix presents the code developed to obtain the weekly benchmarks, serving as a reference range for the current pipeline status.

```
#Import packages
import pyodbc
import pandas as pd
import numpy as np
import scipy.stats as ss
import matplotlib.pyplot as plt
import seaborn as sns
import patsy
import pylab
from scipy import stats
import xlsxwriter
from pandas import ExcelWriter
from pandas import ExcelFile

#Get SQL
server = 'bidw.farfetch.net'
db = 'BI_ANALYTICS'
tb = '[dbo].SCA_Scorecard'
conn=pyodbc.connect('DSN=bidw')

sql = "select OrderlineID, Orderdate_GMT, CheckStockDate,
 ↪ ApprovePaymentDate, DecidePackagingDate, \
        CreateShippingLabelDate, DateStep5_DHL_GMT,
 ↪ ReceivedDate_GMT \
        from BI_DW.dbo.factorderslines where OrderDate_GMT >=
 ↪ '2019-05-19 00:00:00' and OrderDate_GMT <= '2019-05-25
 ↪ 00:00:00' \
        order by OrderDate_GMT "
```

```
#select OrderlineId, SiteName, \
    Step0_CreatedDate_GMT, Step1_StockOK_GMT, Step2_PaymentOK_GMT,
     ↪ Step3_PackagingOK_GMT, \
    Step4_ReadyToSend_GMT, Step5_OrderPickup_GMT,
     ↪ Step6_Received_GMT \
    from [BI_ANALYTICS].[dbo].SCA_Scorecard \
    where Step0_CreatedDate_GMT >= '2019-05-20 00:00:00' "
data = pd.read_sql(sql, conn)
conn.close()

df = pd.DataFrame(data)
pipe = pd.DataFrame(df)
print(pipe)

#Create columns in pipe and set index
pipe['Create_Y_M'] = pipe['Orderdate_GMT'].dt.strftime('%Y%m')
pipe['Create'] = pipe['Orderdate_GMT'].dt.strftime('%Y%m%d%H')
pipe['Step1_out'] = pipe['CheckStockDate'].dt.strftime('%Y%m%d%H')
pipe['Step2_out'] =
 ↪ pipe['ApprovePaymentDate'].dt.strftime('%Y%m%d%H')
pipe['Step3_out'] =
 ↪ pipe['DecidePackagingDate'].dt.strftime('%Y%m%d%H')
pipe['Step4_out'] =
 ↪ pipe['CreateShippingLabelDate'].dt.strftime('%Y%m%d%H')
pipe['Step5_out'] =
 ↪ pipe['DateStep5_DHL_GMT'].dt.strftime('%Y%m%d%H')
pipe['Step6_out'] =
 ↪ pipe['ReceivedDate_GMT'].dt.strftime('%Y%m%d%H')
print(pipe)

#pipeind = pipe.set_index('Create').dropna()
#pipeind = pipe.set_index('OrderlineId').dropna()
#print(pipeind)
#pipeind.dtypes

#Create table Dates
Dates = pd.DataFrame()
Dates['Ranges']=pd.Series(pd.date_range('2019-05-19', '2019-05-26',
 ↪ freq='H'))
Dates['Ranges']=Dates['Ranges'].to_frame()
Dates['Ranges_String'] = Dates['Ranges'].dt.strftime('%Y%m%d%H')
print(Dates)
Dates.dtypes

pipe_test = pd.DataFrame()
pipe_test['OrderlineID'] = pipe['OrderlineID']
```

```
pipe_test['Create'] = pipe['Create']
pipe_test['Step1_out'] = pipe['Step1_out']
pipe_test['Step2_out'] = pipe['Step2_out']
pipe_test['Step3_out'] = pipe['Step3_out']
pipe_test['Step4_out'] = pipe['Step4_out']
pipe_test['Step5_out'] = pipe['Step5_out']
pipe_test['Step6_out'] = pipe['Step6_out']
pipe_test['tmp'] = 1
Dates_test = pd.DataFrame()
Dates_test['Ranges'] = Dates['Ranges_String']
Dates_test['tmp'] = 1
print(pipe_test)
print(Dates_test)

df = pd.merge(pipe_test, Dates_test, on=['tmp'])
df = df.drop('tmp', axis=1)
print(df)

def score(row):
    if (row['Create']<=row['Ranges'] and
     ↪ row['Step1_out']>=row['Ranges']):
        score = 1
    elif (row['Step1_out']<=row['Ranges'] and
     ↪ row['Step2_out']>=row['Ranges']):
        score = 2
    elif (row['Step2_out']<=row['Ranges'] and
     ↪ row['Step3_out']>=row['Ranges']):
        score = 3
    elif (row['Step3_out']<=row['Ranges'] and
     ↪ row['Step4_out']>=row['Ranges']):
        score = 4
    elif (row['Step4_out']<=row['Ranges'] and
     ↪ row['Step5_out']>=row['Ranges']):
        score = 5
    else:
        score = 0
    return score

df['Score'] = df.apply(score, axis = 1)
print(df)

target_tot = pd.pivot_table(df, index='Ranges', columns='Score',
 ↪ values= 'OrderlineID', aggfunc= 'count', fill_value=0)
target_tot=target_tot.rename(columns={0: 'Null', 1: 'Step1', 2:
 ↪ 'Step2', 3:'Step3', 4:'Step4', 5:'Step5'})
print(target_tot)
```

```
min_step1 = target_tot['Step1'].min()
min_step2 = target_tot['Step2'].min()
min_step3 = target_tot['Step3'].min()
min_step4 = target_tot['Step4'].min()
min_step5 = target_tot['Step5'].min()
avg_step1 = target_tot['Step1'].mean()
avg_step2 = target_tot['Step2'].mean()
avg_step3 = target_tot['Step3'].mean()
avg_step4 = target_tot['Step4'].mean()
avg_step5 = target_tot['Step5'].mean()
max_step1 = target_tot['Step1'].max()
max_step2 = target_tot['Step2'].max()
max_step3 = target_tot['Step3'].max()
max_step4 = target_tot['Step4'].max()
max_step5 = target_tot['Step5'].max()

data = [{'Step1': min_step1, 'Step2': min_step2, 'Step3':min_step3,
 ↪ 'Step4':min_step4, 'Step5':min_step5}, {'Step1': avg_step1,
 ↪ 'Step2': avg_step2, 'Step3':avg_step3, 'Step4':avg_step4,
 ↪ 'Step5':avg_step5}, {'Step1': max_step1, 'Step2': max_step2,
 ↪ 'Step3':max_step3, 'Step4':max_step4, 'Step5':max_step5}]
df1 = pd.DataFrame(data)
df1 = df1.rename(index={0: 'Min', 1: 'Avg', 2: 'Max'})
df1

writer = pd.ExcelWriter('OrdersPerStep.xlsx', engine =
 ↪ 'xlsxwriter')
target_tot.to_excel(writer, sheet_name = 'Ranges_OrdersPerStep')
df1.to_excel(writer, sheet_name = 'Min Avg Max')
writer.save()
```

Appendix G

Final Dashboard Views

In this Appendix all developed dashboard views are presented. All displayed values are fictional, for confidentiality reasons.

At the bottom of the weekly, monthly and quarterly views, the graphs' axis were deleted so that the internal targets for the respective metrics, presented as a dotted line, cannot be identified.

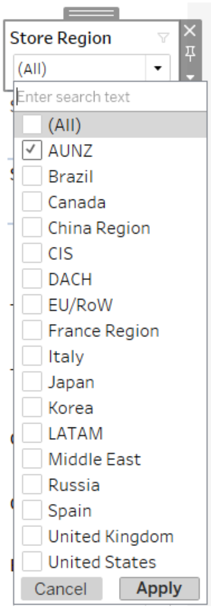

Figure G.1: Detailed view of the functioning of one of the built in filter options

Figure G.2: Dashboard view presenting a weekly view of all metrics

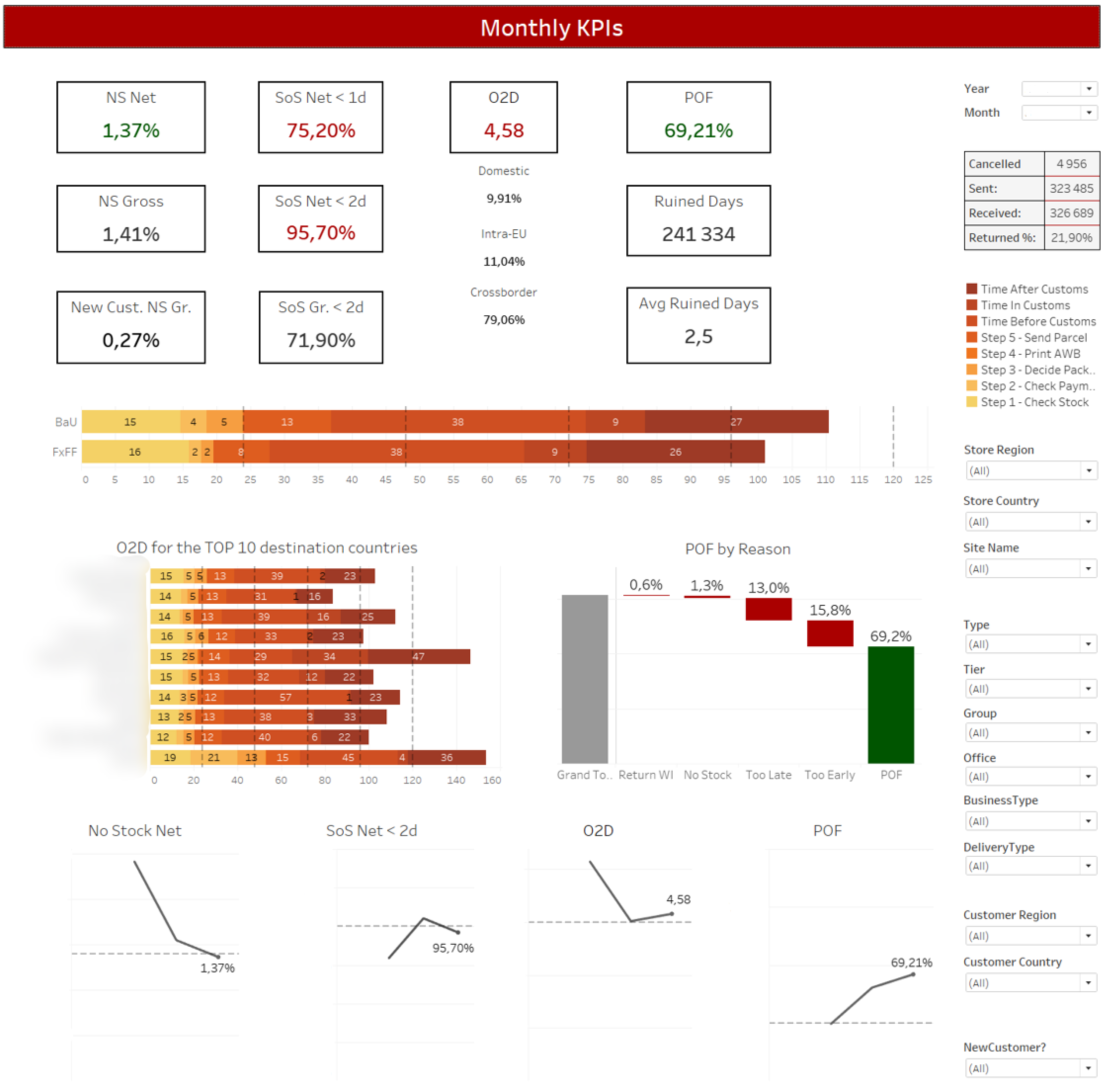

Figure G.3: Dashboard view presenting a monthly view of all metrics

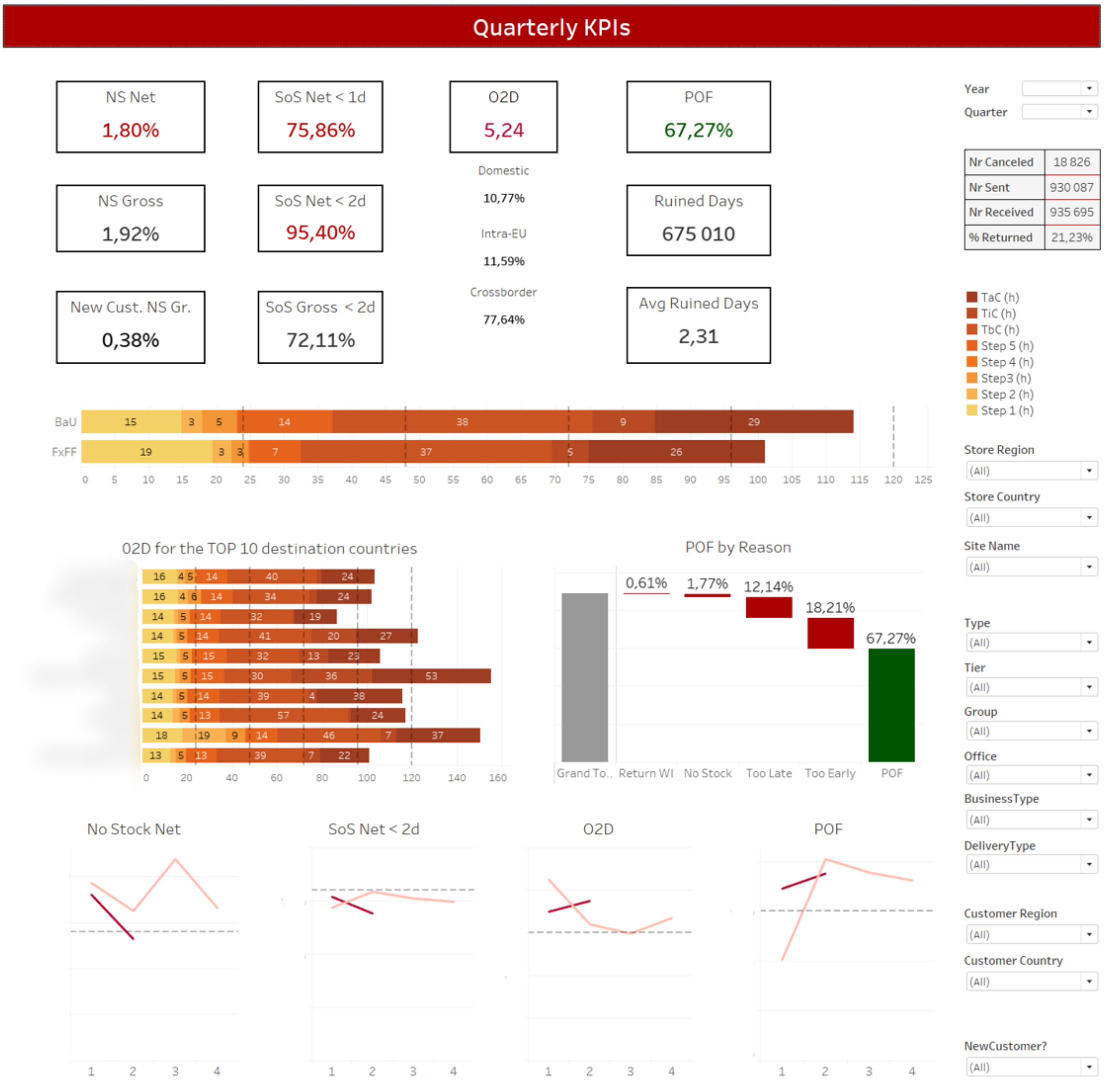

Figure G.4: Dashboard view presenting a quarterly view of all metrics

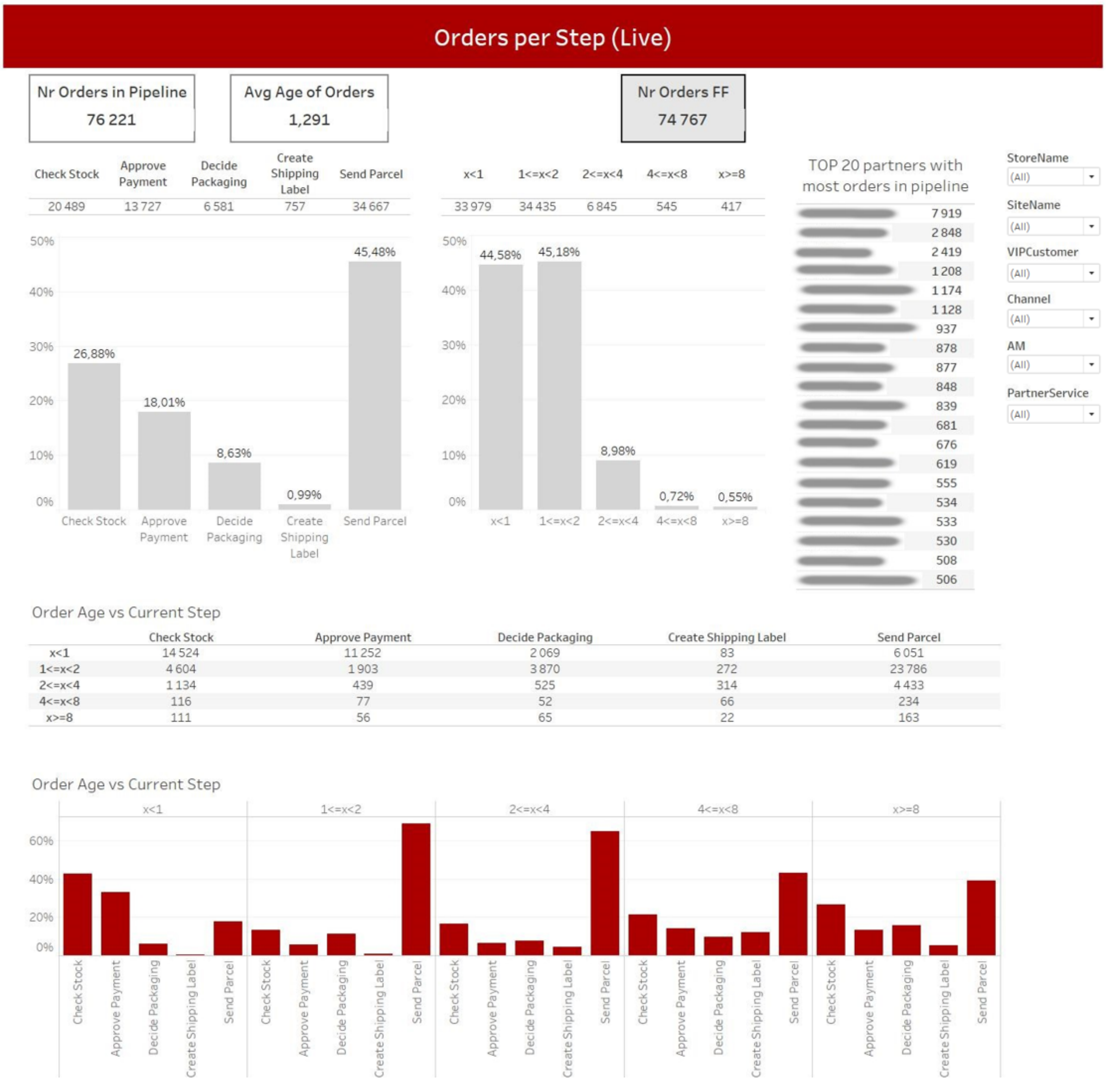

Figure G.5: Dashboard view of the live pipeline status

TOP 20 Partners By Value

Tier (All) | Type (All) | Office (All) | DeliveryType (All) | BusinessType (All) | Year | Week

	Sold ($)	Qty Sold	NS Net	Δ NS Net	SoS Gr. 2d	Δ SoS Gr. 2d	SoS Net 2d	Δ SoS Net 2d	SoS Net 1d	Δ SoS Net 1d	O2D	Δ O2D
[redacted]	134 563	408	0,46%	0,12%	69,61%	-5,95%	98,56%	-0,43%	68,58%	24,34%	4,73	0,26
[redacted]	60 312	106	0,76%	0,11%	54,41%	-17,24%	91,18%	-8,82%	31,62%	11,93%	5,27	0,44
[redacted]	42 727	154	0,00%	-0,28%	62,29%	-18,25%	99,43%	0,03%	73,14%	-9,79%	4,90	0,56
[redacted]	28 859	82	0,00%	0,00%	73,81%	-15,28%	100,00%	0,00%	86,90%	-0,37%	5,73	-0,12
[redacted]	21 824	34	1,52%	1,52%	82,35%	3,66%	100,00%	16,39%	100,00%	21,31%		
[redacted]	18 631	78	2,56%	-20,51%	53,95%	-7,25%	88,16%	9,05%	39,47%	14,10%	4,98	-0,63
[redacted]	18 039	48	0,00%	-1,30%	64,18%	-23,96%	100,00%	1,69%	85,07%	2,02%	4,50	-0,01
[redacted]	17 217	76	0,00%	0,00%	60,67%	-21,47%	97,75%	4,00%	61,80%	1,98%	5,15	0,88
[redacted]	17 106	48	0,00%	-1,45%	74,47%	-15,85%	93,62%	-6,38%	87,23%	-12,77%	4,23	-0,23
[redacted]	13 591	23	0,00%	-2,44%	78,26%	-8,23%	100,00%	0,00%	91,30%	23,74%	4,77	0,19
[redacted]	13 347	46	2,00%	0,84%	67,39%	-19,75%	97,83%	0,68%	82,61%	5,47%	4,38	0,01
[redacted]	11 928	35	0,00%	0,00%	68,29%	-9,97%	97,56%	4,08%	85,37%	11,45%	4,61	0,48
[redacted]	10 331	26	3,13%	-1,64%	61,76%	-3,95%	100,00%	2,86%	76,47%	-0,67%	4,85	0,20
[redacted]	10 163	26	0,00%	-2,38%	78,13%	-13,77%	100,00%	0,00%	81,25%	5,57%	4,33	0,30
[redacted]	9 729	35	0,00%	0,00%	52,27%	-38,11%	97,73%	-2,27%	34,09%	-33,22%	4,67	0,08
[redacted]	9 398	22	0,00%	0,00%	66,67%	-24,03%	96,30%	-3,70%	66,67%	-14,73%	4,67	0,27
[redacted]	9 200	22	0,00%	0,00%	80,95%	-19,05%	100,00%	0,00%	100,00%	0,00%	6,19	0,10
[redacted]	8 615	26	2,33%	2,33%	63,64%	13,64%	90,91%	13,13%	60,61%	32,83%	4,84	-0,26
[redacted]	8 275	33	5,71%	5,71%	33,33%	-45,05%	66,67%	-30,63%	39,39%	-30,88%	4,68	-0,42
[redacted]	8 043	28	0,00%	-2,17%	58,82%	-27,84%	100,00%	0,00%	55,88%	-15,23%	4,94	0,33

TOP 10 Partners By Impact

NS

	Qty Sold	NS Net
[redacted]	25,0	13,33%
[redacted]	46,0	6,12%
[redacted]	13,0	16,67%
[redacted]	2,0	100,00%
[redacted]	78,0	2,56%
[redacted]	24,0	8,00%
[redacted]	33,0	5,71%
[redacted]	410,0	0,46%
[redacted]	14,0	11,11%
[redacted]	3,0	50,00%

SoS

	Sent	SoS Net 2d
[redacted]	34,0	58,82%
[redacted]	20,0	35,00%
[redacted]	136,0	91,18%
[redacted]	33,0	66,67%
[redacted]	76,0	88,16%
[redacted]	19,0	52,63%
[redacted]	488,0	98,57%
[redacted]	19,0	68,42%
[redacted]	24,0	75,00%
[redacted]	12,0	50,00%

O2D

	Received	O2D
[redacted]	536,0	4,73
[redacted]	272,0	4,87
[redacted]	171,0	4,81
[redacted]	136,0	5,27
[redacted]	86,0	5,73
[redacted]	90,0	4,98
[redacted]	78,0	4,50
[redacted]	80,0	4,34
[redacted]	68,0	4,35
[redacted]	46,0	5,98

POF

	NrOrdersPOF	Partner POF
[redacted]	8 279	86,74%
[redacted]	3 247	81,96%
[redacted]	1 746	78,44%
[redacted]	1 821	82,15%
[redacted]	1 464	71,35%
[redacted]	1 161	79,21%
[redacted]	813	90,83%
[redacted]	889	89,04%
[redacted]	610	89,81%
[redacted]	598	74,13%

Figure G.6: Dashboard view presenting the selected week's top 20 partners by value metrics, as well as the top 10 partners by impact per metric

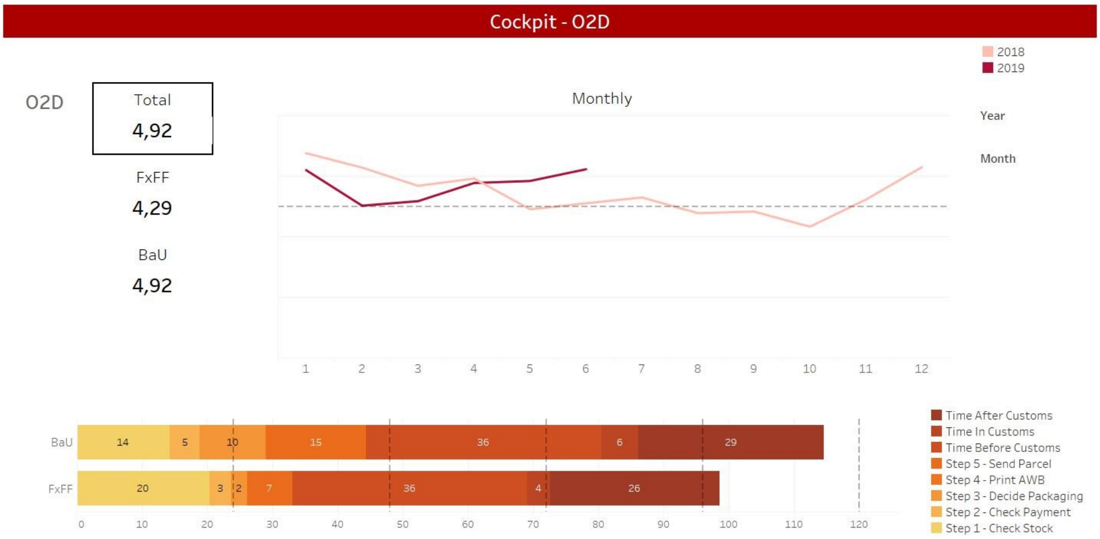

Figure G.7: Ops Cockpit - O2D

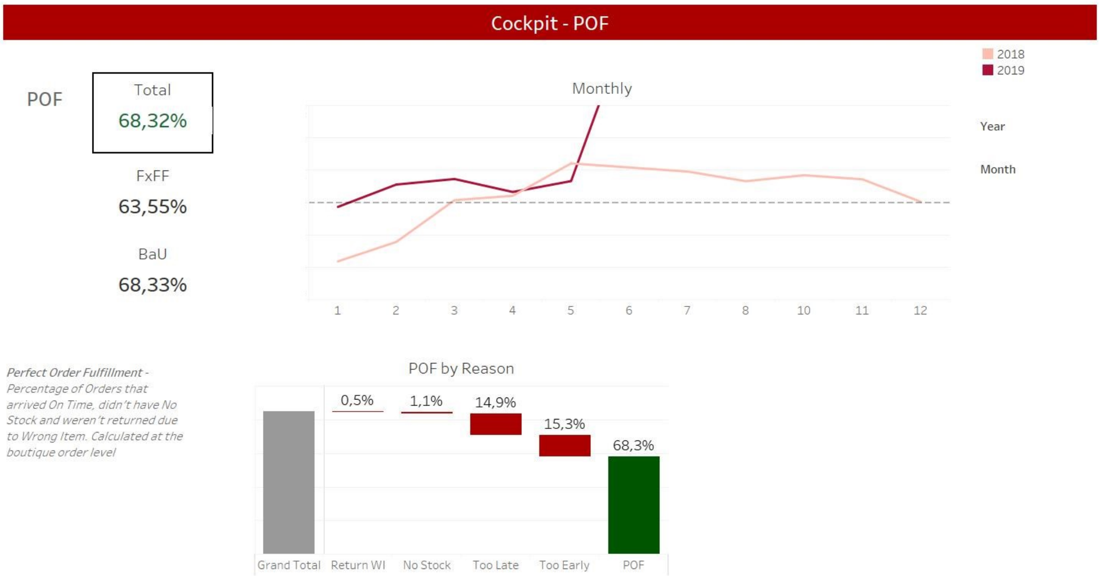

Figure G.8: Ops Cockpit - POF

Figure G.9: Ops Cockpit - RD

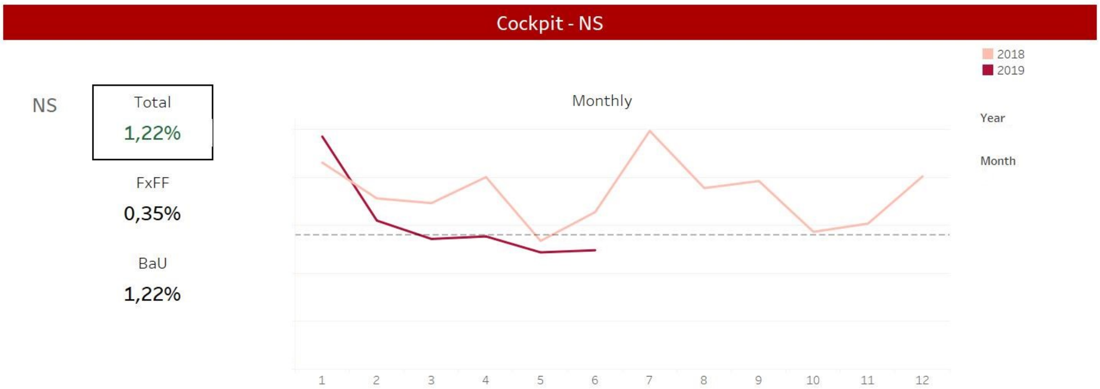

Figure G.10: Ops Cockpit - NS

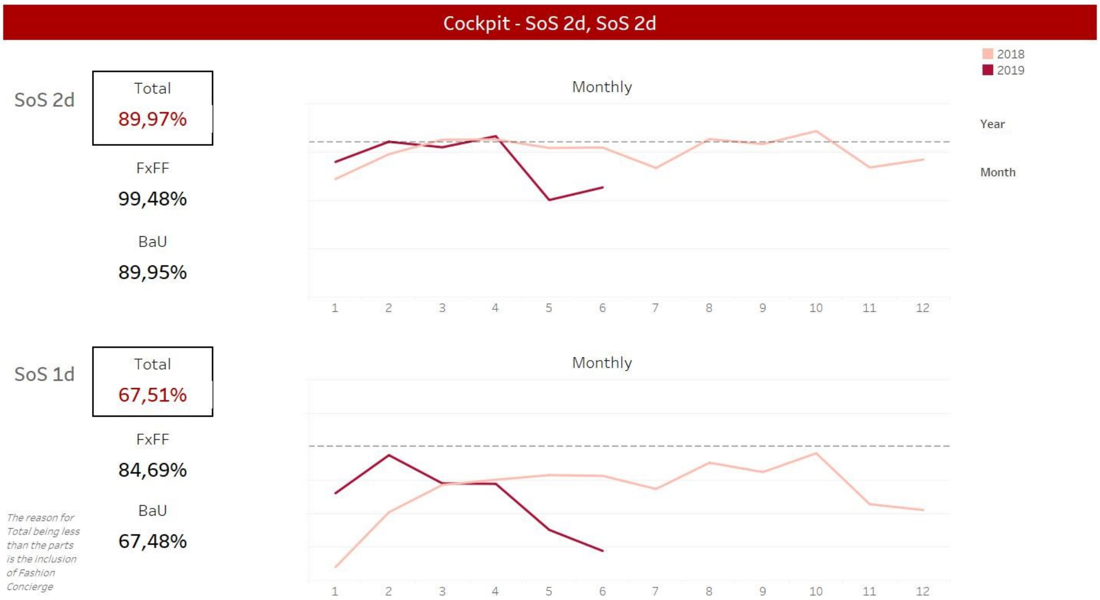

Figure G.11: Ops Cockpit - SoS

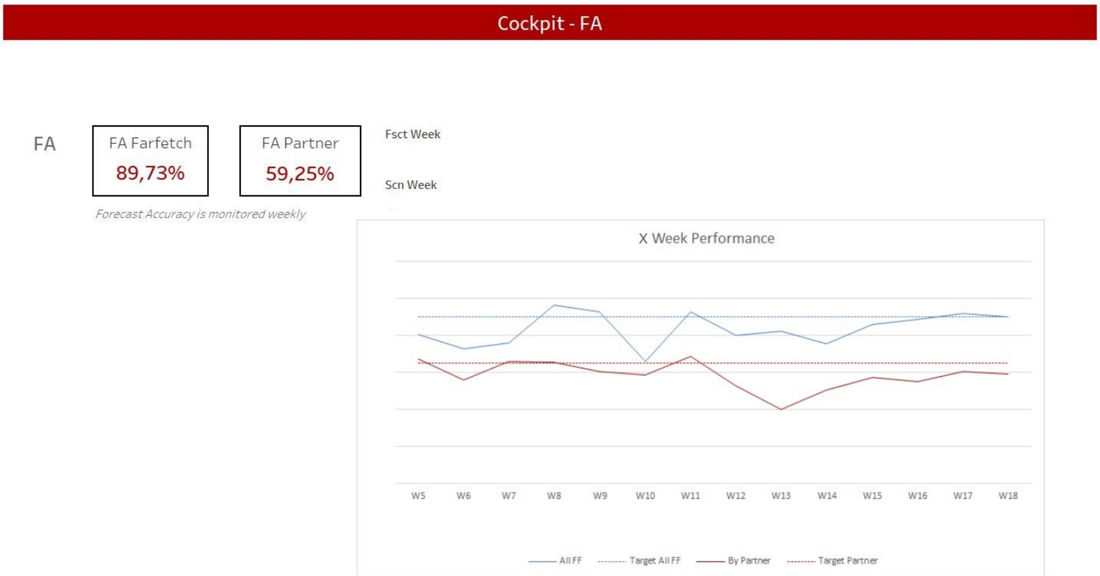

Figure G.12: Ops Cockpit - FA