ADDIS ABABA UNIVERSITY COLLEGE OF BUSINESS AND ECONOMICS

Big Data Analytics: Examination of Export, Import and DnD Datasets Through Advanced Data Visualization
The Case of Maersk Ethiopia Plc

A Research Project Submitted to EMBA Program

Presented in Partial Fulfillment of the Requirements for Master of Arts Degree in Executive Master of Business Administration.

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DECLARATION

The undersigned declares that this research project, “Big Data Analytics: Examination of Export, Import and DnD Datasets Through Advanced Data Visualization: The Case of Maersk Ethiopia Plc” is his original work and it has not been submitted for any degree or examination in any other university. In addition, all sources of materials used for the study have been duly acknowledged. The undersigned strongly declares that he obtained the necessary authorization and consent to carry out this research.

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This is to Certify that the Research Project prepared by Yalkewyihun Eshetu, entitled: “Big Data Analytics: Examination of Export, Import and DnD Datasets Through Advanced Data Visualization: The Case of Maersk Ethiopia Plc” submitted in partial fulfillment of the requirements for the degree of Degree of Master of Arts (Executive Master of Business Administration) complies with the regulations of the University and meets the accepted standards with respect to originality and quality

Signed by the Examining Committee:

Examiner: ________________ Signature: ______________ Date: ______________

Examiner: ________________ Signature: ______________ Date: ______________

Advisor: __________________ Signature: ______________ Date: ______________

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Abstract

In this era of Big Data, companies arrive at a decision based on objective and unbiased information- Data. Companies need to find the means and capabilities to analyze datasets that have been acquired for years. Leveraging their datasets at their fingerprints, leaders can make decisions backed by verifiable data. The traditional Business Intelligence capabilities lack the sophistication and flexibility to analyze larger datasets to discover meaning and insights that have otherwise remained hidden interactively. Big data analytics techniques such as Advanced Data Visualization, are efficient and easy to examine large and complex datasets to discover actionable insights. The Transportation and logistics sectors are among the most advantageous sectors to take advantage of the advanced analytical tools and Big data technologies available to examine their datasets. This study, Big Data Analytics: Examination of Export, Import and DnD Datasets Through Advanced Data Visualization: The Case of Maersk Ethiopia Plc, examined the Export and Import datasets from 2010 to 2020 and DnD Datasets for the year 2016-2020. The goal of the study was to extract meaning and insights and describe the results using data visualization and analytics technique. The selected case company, Maersk Ethiopia Plc, is a fully owned consultancy entity of Maersk A/S, a Shipping and Logistics company, in the Ethiopia Business area. A quantitative method approach to analyzing the secondary data obtained from the case company via a business intelligence tool WEBI and CXED tool was chosen in line with the research objective. Based on the research purpose, a descriptive case study design was chosen to describe the study's results. The data analysis was performed utilizing an advanced data visualization tool, Tableau. Several visualization charts of the tool were utilized in describing the results. Analyzing a larger dataset using data visualization was helpful to see trends in the various Trades, the commodities with higher contribution, the customers' performance, the demand for Reefer containers, the DnD revenue performance, the Turn time and Free time along with the detention bucket of the returned containers.

KEY Words- Big Data & Analytics, Advanced Data Visualization, Tableau, Export, and Import datasets, DnD datasets, Maersk Ethiopia plc.

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Praise to the Lord.

Yalkewyihun Eshetu

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ACRONYMS

Acronyms	Definition
API	Application Programming Interface
ATF	After the Fact
BI	Business Intelligence
BOXI	Business Objects Xi
BTN	Brussels Tariff Nomenclature
BW	Business Warehouse
CGMA	Chartered Global Management Accountant
CRM	Customer Relationship Management
CXED	Calculation Easy at Demurrage
CY	Contribution Yield also CYield
DA	Data Analytics
DDDM	Data-Driven Decision Making
DJ	Djibouti
DSS	Decision Support Systems
DV	Data Visualization
EAA	Easter Africa Area
EIS	Executive Information Systems
ES	Enterprise Systems
ET00	Ethiopia Business Area Code
FIP	Freighters International (PABOMI) Plc
FT	Free Time
GCSS	Global Customer Service System
GDP	Gross Domestic Product
HDFS	Hadoop Distributed File System
HOA	Horn of Africa
IBM	International Business Machines Corporation
INFORMS	Institute for Operations Research and The Management Science
IT	Information Technology

K	Kilo (1000), Thousand
KPI	Key Performance Indicator
MECL1	Service for West Central Asia to North America-Westbound
MET	Maersk Ethiopia Plc
MLL	Maersk Line Limited
MOOCS	Massive Open Online Course
MS	Microsoft
MSL	Maersk Line
OLAP	On-Line Analytical Processing
OR	Operations Research
POD	Place/Port of Delivery
POR	Place/Port of Receipt
R	programming language and free software
ROI	Return on Investment
SaaS	Software as a Service
SAP	Systems Applications and Products Company Name
SCL	Safmarine Line
SCM	Supply Chain Management
SOW	Share of Wallet
SQL	Structured Query Language
TPA	Third Party Agent
USD	United States Dollar
W5	Trade Name for Intra Africa
WEBI	Web Intelligence
Z1	Trade Name For: Americas - East Africa
Z2	Trade Name For: Far East - East Africa
Z3	Trade Name For: Middle East - East Africa
Z4	Trade Name For: Europe - East Africa
Z8	Trade Name For: Far East - Horn of Africa

Chapter 1 **INTRODUCTION**

Introduction

This chapter discusses background of the study and the study area, statement of the problem, objectives of the study, significance and scope of the study, definition of key terms, and organization of the study.

1.1 Background of the Study

"We need to make Data-Driven Decisions!"- a common buzzword phrase in the corporate world. A word so simple but comprising complicated activities such as identifying KPIs, gathering measurable data, analysis of the data to come up with valuable and actionable *insights* for business growth(Schrack & Warner, 2020)

In today's business, decision-making is progressing toward the practice of first understanding the numbers and what they reveal and then using that 'insight' (the knowledge, learning, understanding generated from business analytics) to make informed business decisions. This approach replaces the practice of doing what feels right first and then looking at the numbers to see if it succeeded(CGMA, 2016).

Storage capacity and data gathering methods and techniques have changed considerably due to technological advancements, making enormous Data readily available. Every second, a massive quantity of new Data is created from various sources, necessitating innovative data storage and analysis methods to extract as much value as possible from the massive data sets (Elgendy & Elragal, 2016).

Big data refers to the vast amounts of structured and unstructured data that organizations can collect and use to analyze it in a meaningful way. The need to analyze these datasets resulted in the development of new techniques and methods (in data science and management) for analyzing and extracting actionable insights(Storey & Song, 2017).

The Transportation and logistics sectors are among the most advantageous sectors to take advantage of the analytical tools and technologies available to them. With the continuous emergence and evolution of Big Data, these sectors can collect and manage vast volumes of data daily. Content, location, weight, size, source and destination, and a variety of other data are tracked and collected for millions of deliveries and shipments around the world every day, presenting multiple opportunities for using Big Data analytics to harvest all of this large-scale data and provide new opportunities in terms of service quality and operational efficiency (Borgi et al., 2017).

One of the Big data analytics techniques is Advanced Data Visualization (ADV) (Russom, 2011). According to Russom, ADV techniques when applied to large volumes of data that an enterprise has not yet tapped for analytics, can help discover actionable insights or new facts that no one knew before. According to the author, ADV tool such as Tableau is an easy and efficient way to analyzed large datasets for insight discovery.

Insights that are backed by data provide objective and unbiased information to all internal and external customers, which is of great importance and value. Analysis of a larger dataset provides decision-makers to view patterns and trends that were otherwise remained hidden. Taking Maersk Ethiopia plc as a case, this study, applying Big Data Analytics, examined the Export, Import and Demurrage and Detention (DnD) datasets thorough Advanced Data Visualization tool, Tableau.

1.2 Company Background

Maersk A/S (A.P Moller Maersk or Maersk) is an integrated shipping and logistics company founded in 1904 in Denmark. Operating now in more than 130 countries, it employs around 80,000 people and remains a giant in shipping and logistics services. Maersk had recognized total revenue of USD 39.8 Billion in the year 2019. Its headquarters is based in Copenhagen, Denmark and through its regional office in South Africa, manages its activities in Africa

Maersk's presence in Ethiopia started in 1994, represented by its long-term Third-Party agent (TPA) Freighters International PABOMI plc (FIP), a local company with decades of experience in shipping and forwarding industry in Ethiopia. Later in the year 2007, a wholly-owned foreign consultancy office, Maersk Ethiopia Plc (MET), was established in Addis Ababa, Ethiopia, to serve the former Horn of Africa countries (HOA) Sudan, Djibouti, Kenya, and Ethiopia in coordinating, exploring, and assessing market performance in the area.

MET was established to engage in Management Consultancy, Marketing in Airfreight and Depot Services, shipping line business, and documentation as per the Ethiopian Investment Proclamation in 2007. Since 2016 MET has been under the larger Eastern African Area (EAA) radar, one of the six areas (Clusters) in Africa, comprised of countries, Djibouti, Ethiopia, Kenya, Sudan, Tanzania, Rwanda, Burundi, and Uganda under the current geographical setup of Maersk in Africa.

The activities of MET are limited and focused on consultancy services it offers to Maersk (head office), Maersk South Africa (Region Office), Djibouti, Kenya (headquarter for EAA), and Maersk's TPA in Addis Ababa. It runs a full organization of Sales, Customer Service, Finance, and Administration staff highly focused on consultancy services on both import and export activities of Ethiopia area.

MET plays a greater role in evaluating the Ethiopia Market in detail to provide Maersk and other countries in the EAA with actionable insights. Its focus areas include Market analysis on the Import and Export activities, analysis on profitable cargo and ports, Analysis of the Demurrage and Detention (DnD) Revenue, and market analysis for potential growth and expansion on the land side activities (logistics services). It works wholly with Ethiopian Shipping and Logistics Services Enterprise (ESLSE), the government-owned and the only shipping line of the country, for coordinating all import activities and with the TPA for all Export and related activities.

1.2.1 Ports, Services, Trades in Ethiopia Business Area

Ports: Currently, the main gateway for Ethiopia handling over Ninety-five percent of cargo transported via sea is the Port of Djibouti. Despite its costliness compared to other ports in the region, the port maintains modern infrastructure (Port and Railway) as an advantage. Port of Berbera and Mombasa are other gateways for some of the imports to the country used by Maersk.

Djibouti (Port of Djibouti) is the main maritime passage and a main trading route between East and West. Djibouti's strategic location contributed for the rise of the port as a regional hub for the Red Sea and Indian Ocean and in a wider context the three continents Europe, African and Asia.

Services: Up to the year 2016, Maersk had three services in the Horn of Africa, namely, HOA service, 28 A service, and MECL, calling to Djibouti port, Port Sudan, and Mombasa ports. Later these services were reviewed to Blue Nile Express-Dedicated for Export and MECL1 services- handling Import shipments in the Ethiopia Business area.

Trades: With the above two services, Maersk serves the major trades or routes facilitating the Import and Export activities. The trades are W5 (Intra Africa), Z1 (Americas - East Africa), Z3 (Middle East - East Africa), Z4 (Europe - East Africa), Z8 (Far East - Horn of Africa), and finally, Z2 trade mainly serving the port of Mombasa (Far East - East Africa).

1.2.2 Maersk's Export and Import Shipments Overview in Ethiopia Business Area

Export is the processes transporting a cargo from the country of origin i.e. Ethiopia to other ports in the world. Since Ethiopia is the only land locked country in the Horn of Africa, Port of Djibouti is the main gateway or Port/Place of Receipt (POR) for almost all export cargos. Due to the agrarian nature of the country, majority of the export commodities are agricultural product. Commodities shipped by Maersk include: Coffee, Sesame seeds, Pulses Apparel/garment products, and minerals. Raw hides and Skin, and Meat products are other export commodities shipped by the Carrier. Export market share for Maersk ranged between 36% and 43 % in the last five years (Maersk, 2021).

Import: refers to the activities of transporting goods or cargos from POR to Place/ Port of Discharge (POD) i.e. from other Ports in different corners of the world to Ethiopia via Port of Djibouti. Import commodities mainly include Foodstuff, Machineries, textile, and palm oil amongst other commodities. Import market share for Maersk ranged between 23% and 49 % in the last five years (Maersk, 2021). Currently the

Import Cargo by sea (Vessels) is monopolized by the only government shipping line of the country, Ethiopian Shipping and Logistics Service Enterprise (ESLSE). Maersk works with ESLSE on a tender (slot hire) basis that gets renewed every Six months or yearly as required. Maersk's Share of wallet (SOW) from the ESLSE's Import Business ranged from 26 % and 49 % in the last five years (Maersk, 2021).

Other Non-ESL Import shipments is dominated by Aid shipments from the USA, Projects Commodities (Massive project machineries) by Ethiopian Government. This business segment is highly affected by the availability of foreign currency and availability of ongoing or new projects by the government of Ethiopia. The Country's political and environmental situations significantly influences the Aid shipment volume of the segment.

1.2.3 Demurrage and Detention (DnD)

Maersk as a containerized cargo mover by sea, offers its customers containers to load their cargos. These containers are provided to customers free of charges for a pre agreed number of days, 'Free time.' Free time refers to days that the customers are given to hold the containers without any payment. Once these free days elapse a combined charge known as Demurrage and Detention (DnD) is charged by Maersk. Failure to clear the cargos from the ports and failure to return the containers with the free time by the customers will result in these charges. The containers Turn time therefore will have significant impact on the total revenue of this revenue segment.

The types of containers manly used by customers in the Ethiopia business area are mainly 20 Feet (20 TEU), 40 Feet (40 FEU) and refrigerated container (Reefer Containers). While Reefer containers are used for perishable cargo types that need to be stored in a cool environment as per the required standards, DRY cargos are loaded without such requirement in the mentioned container sizes.

MET's sales and finance team are responsible for monitoring the Import, export and DnD performance in the Ethiopia Business Area. The departments closely work with region, area office and the HQ in Copenhagen to Serve the Customers better. The analysis of the performance of the above segments are used as inputs for setting targets, budgeting, tender with ESL and to resolve issues that customers face while shipping with Maersk.

As previously stated, the datasets contain important information about the customers' commodities, POR, POD, the preferred Cargo type and container sizes, the free time and turn time of the containers over the years. Analysis of these customers' details over a relatively larger period is of great importance to extract patterns and trends per trade, POD, POR and to identify those commodity types, container types and sizes with higher volume of shipment and revenue contribution. The analysis of these datasets can reveal relationships that may have existed but might have been missed. Understanding what is happening in the organization is the first step to find out why things are the way they are and what needs to be done to influence positive business outcome in the future.

This study, taking MET as a case, intended to examine Export, Import and DnD datasets applying Big Data Analytics technique: Data visualization, to extract actionable insights. The examination of the datasets was based on FFE(Volume) Trend, Trade/Routes, container type and Size, Free time, Turn time, and DnD Revenue Trend.

1.3 Statement of the problem

A giant in the shipping and logistics sector, Maersk, has been generating and acquiring data for over 100 Years. This vast amount of data can leverage understanding the business, the customers, and their needs to offer new products and services and perform business and strategic decisions if used in the right way and with the right tools.

Maersk's strong BI foundation makes it possible to access data and data integration with the various systems in several countries and overseas offices. Countries in their respective areas (cluster or business units) can utilize the vast data gathered for their operational and managerial decision-making. However, the BI capabilities in Maersk Ethiopia Plc (MET) are being utilized for reporting purposes mainly and analysis of the reports are limited to yearly, quarterly, or actual versus target comparison that is done via MS Excel.

For instance, the sales consulting team's analysis of the Export and Import datasets is limited to trades/route performance that mainly considers Volume (FFE) as the basis of the analysis. The analysis of the datasets is also limited to short period of time that doesn't exceed more than a year. Most of the time trade performance is compared with the ROFO (Rolling Forecast) and the L4W (the last Four Weeks Average) to compare actual versus target for a specific week. However, such analysis is short sited and is targeted to analyzing and meeting the KPI's or targets set in advance.

Taking the Finance teams that primarily monitors the DnD revenue performance, the analysis or examination of the datasets focuses on the actual revenue versus target, that's again compared to previous year and the targets set. Due to the big size of the DnD datasets mainly because it contains list of containers loaded (one to hundred containers per booking Number and hundreds of thousands per year) and the limited capability of excel to analyze the datasets, the analysis is narrowed to a shorter period of time same as in the Export and Import datasets analysis.

The above mentioned challenges i.e. the limited capability of the BI tool used for reporting purpose, the analysis of the import and Export datasets based on KPIs and targets and the limited capability of the MS Excel to analyze large DnD datasets needs to be addressed if Maersk needs to extract value from its large datasets acquired over the years. The datasets contain important detailed information about the customers, the commodities shipped, the year, month or week, the trades (combination of the load port and discharge ports), rates, Revenue and contribution Yield per cargo, the container size and type, amongst other information if analyzed the right way can reveal valuable actionable insights.

Experts in the field of Big Data analytics, affirm that, analyzing massive datasets with advanced analytics tools and techniques rather than smaller samples processed and analyzed with spreadsheets adds significant value to decision making. Advanced Analytics, via revealing valuable hidden insights, can significantly reduce risks and improve decision-making (Manyika et al, 2011, as cited in Elgendy & Elragal, 2016).

Even though the large datasets can be acquired from the company's data warehouses, finding the right tool and techniques to analyze the large datasets calls for another challenge to be addressed. According to Sadiku et al. (2016), Data Visualization (DV) has developed as a powerful and widely applicable technique for analyzing and understanding big and complicated data sets. It has evolved into a quick and simplistic way of communicating information in a universal format. Because “a picture is worth a thousand words.”, visualizing the data than the usual, smaller size, in tables or bar charts in an interactive and flexible manner, differentiated by colors and sizes, is believed to be an easy and efficient method to extract insights from large datasets, by experts in the field.

Therefore, this study attempted to address the challenges by examining a large dataset of the Export and import, and DnD datasets using an advanced data visualization and analytics tool, Tableau, to extract/discover meanings and insights.

1.4 Research Questions

The research questions were set to examine the most important aspect of the case company's business and what the data can reveal about the overall performance of the case company. Therefore, the following research questions were answered by the research:

1. What is the volume (FFE) trend for Import and Export shipments per Trade for the year 2010- 2020?
2. What commodities have a higher contribution yield for Import and Export per Trade for the year 2010- 20202?
3. What’s the Top 10 customers’ performance for Import and Export in FFE for the year 2010-2020?
4. What month, or week has the highest demand for Import Reefer (Refrigerated) containers for the year 2010-2020?
5. What is the DnD revenue trend per Container Size for the year 2016- 2020?
6. What is the Turn Time and Free Time trend and the ‘detention bucket’ for the returned containers for the year 2016-2020?

1.5 General Objective

Taking Maersk Ethiopia Plc (MET) as a case, the general objective of the study is to examine Export, Import and DnD Datasets using an Advanced Data Visualization technique and tool to extract meaning and insights and to describe the results.

1.5.1 Specific Objectives

The research had the following specific objectives:

1. To examine and describe the volume (FFE) trend for Import and Export shipments per Trade for the year 2010- 2020.
2. To examine and describe what commodities have a higher contribution yield for Import and Export per Trade for the year 2010- 2020.
3. To examine and describe top 10 customers' performance for Import and Export in FFE for the year 2010-2020.
4. To examine and describe the month, or week that has the highest demand for Import Reefer (Refrigerated) containers for the year 2010-2020.
5. To examine and describe the DnD revenue trend per Container Size for the year 2016- 2020
6. To examine and describe the Turn Time and Free Time trend and the 'detention bucket' for the returned containers for the year 2016-2020.

1.6 Significance of the Study

Data is being considered the raw materials of the 21st century available in abundance. Therefore, the means & capability to handle & extract value & knowledge from the datasets need to be studied & provided (Elgendy & Elragal, 2016). Information significantly improves the quality of Decision making as well as the performance of the decision-makers.

Organizations' ability to process massive amounts of data for their success has become vital than ever before. Yet, many organizations are still lagging. According to, Davenport and DalleMule (2017) less than half of an organization's structured data and less than a percent of its unstructured data is actively used in decision-making. An indication of companies' struggles to use their available Data effectively for decision-making can be recognized from PricewaterhouseCoopers' survey. The impeding factors were a) lack of data-driven skills and analytical talent (54%), b) data silos (51%), and c) unreliable data (50%) (*Pwc, 2019*).

To address the lack of the required skills and talents (one of the impeding factors), according to Mention (2019), some companies hire a data scientist. However, a better and long-term solution would concentrate on building in-house skills to develop "data literates." where They can effectively use advanced analytics and visualization solutions such as Tableau, SAP, and Google Data Studio (to mention some).

Therefore, this study be a pilot project to see what the datasets hold that can improve decision making. The results can be used to show the values of effectively analyzing data to obtain meaningful insights. It is also believed to contribute to the data literacy of the Easter Africa Area in general and Maersk Ethiopia plc.

Besides the requirement of being an academic exercise for the partial fulfillment of the EMBA program, the additional important significance of the study can be used as a baseline for future case studies in the related theme. Since there have been no previous studies made on the subject matter that the researcher could locate in the Ethiopian context, the study can inspire future researchers to explore in greater depth and to come up with an even better outcome.

1.7 Scope of the Study

The study focused on analyzing 11 years' Export, Import and DnD Datasets using an advanced Data visualization technique and tool in Maersk Ethiopia Plc. Big data analytics/Advanced analytics cover a broader area of analytics such as artificial intelligence, natural language processing, data mining, statistical and complex SQL capabilities. The study considered only advanced data visualization technique and tools to analyze the datasets. The datasets are selected were structured Import and Export shipments and DnD datasets.

1.8 Limitations of the Study

The analysis of the dataset was only limited to Import and Export shipment based on attributes in Shipment Summary and DnD datasets which are based on Structured data extracted from WEBI (Web Intelligence), an SAP BI platform. The concepts of Big Data/advanced analytics according to experts in the field is believed to contribute at a larger scale and types of data (semi structured and unstructured) and from various sources. Due to time, technology and skill limitation, the study is narrowed to structured and 11 years' datasets.

Another limitation of the study is other than considering the important factors such as volume, Trade, Revenue, container type and Size, etcetera, for the analysis, the research didn't not cover if there existed any relationship between the above mentioned variables and hence compromising the quality of the research to some extent.

1.9 Definition of Terms

Consignee	The individual or firm specified on the Bill of Lading and legally authorized to receive the shipped goods
Contribution Yield	The Contribution Margin of a shipment plus/minus Flow adjustment. Abbreviated CYield or CY.
Detention Bucket	A grouping of days with in which the returned containers fall in. e.g. "1-7 days,", "More than 30 day"
DnD	charges payable when the Customer holds Carrier's Container beyond the agreed period of Free Time for the combined period of inside and outside the terminal, port, or depot.
Export	Cargo shipped and delivered to other countries
Free Time	the period agreed between the Shipping line and the Customer for which Demurrage and Detention is not be paid by the Customer
Freight	The price paid to the carrier for the transportation of goods or merchandise by sea from one place to another

Import	Cargo shipped and brought in from to other countries
Shipment	the specific movement of a consignment from origin to destination
Shipper	A person or company at origin who books a shipment of cargo to the consignee at destination Can also be known as Consignor
Trade	A pair of two Geo-Regions and the direction defines the Trade - for e.g. Z1, Z2, Z8 also referred as Route
Turn Time	The total number of days with in which the customers return the containers.
Volume	The number of Containers shipped in FFE

1.10 Organization of the Study

The study is organized into five chapters. Chapter one introduces the study and background of study which provides information on the research problem, objectives, scope, limitations, significance of the study. Chapter two discusses Data, Business Intelligence, Business Analytics, data visualization, and advanced visualization tools. In Chapter three the research methodology adopted for the study and relevant justifications is discussed. Chapter four presents the findings and results of the study. Chapter five presents the conclusion, summary of major findings, and recommendations.

Chapter 2 LITERATURE REVIEW

2.1 Introduction

In this chapter, a review of literature on Big Data Analytics was conducted. The review included Big Data Analytics, Data Visualization tools and techniques. The review covered areas of Business Intelligence and Business Analytics, the need for analytics and its relationship with Data Driven Decision-Making. The researcher explored Internet resources, Company's web portals related to Data Analytics and technologies, books, and articles.

2.2 Big -Data, Information and Knowledge

Private and public organizations are under pressure to adjust swiftly to changing circumstances. The business environment (*markets, consumer demands, technology, and society*) is continually evolving and getting increasingly complex, compelling them to adapt to the new environment and innovation in their operations. These operations demand agility and the ability to make daily and strategic, tactical, and operational decisions (Sharda et al., 2014, p.2). Making such decisions may necessitate a significant quantity of data, information, and knowledge. Processing these in the context of the required decision must be done quickly, often in real-time, and with the help of computers(Sharda et al., 2014, p.2).

2.2.1 Data

Regardless of how simple it may appear, Davenport and Prusak (1998) emphasized the importance of understanding what Data, Information and Knowledge mean to decide what organizations need for use. According to the authors, Data is "a set of discrete, objective facts about events." with little importance or meaning. For example, a purchase transaction does not tell why the purchase was made other than the type, quantity, or amount paid.

Data can be obtained from internal and external sources. Enterprise resource planning (ERP) databases and customer relationship management (CRM) systems are examples of internal and external sources of Data respectively (Nykänen et al., 2016). Based on its type or form, Data is categorized into Structured-Data: -information that is standardized, fixed and can be read or understood by computers, Semi-Structured, and Unstructured-Data: - information that is not easily understood by computers & in several forms such as text, document. Video, and pictures (Heang & Mohan, 2017).

Data collected based on the type of data obtained can be classified into three. According to Kumar, (2017.p 34) Cross-Sectional Data refers to data collected on various variables of interest during or over a period of time. (e.g., Data about a movie's budget, actors, genre, directors, in 20xx). When Data is collected based on a single variable, demand for a specific item such as laptops or smartphones, for example, over several time intervals (weeks, months), is referred to as Time Series Data. Panel Data or longitudinal Data is data collected with multiple dimensions or several variables over several time intervals. (GDP or unemployment rate of several countries, for, e.g.)

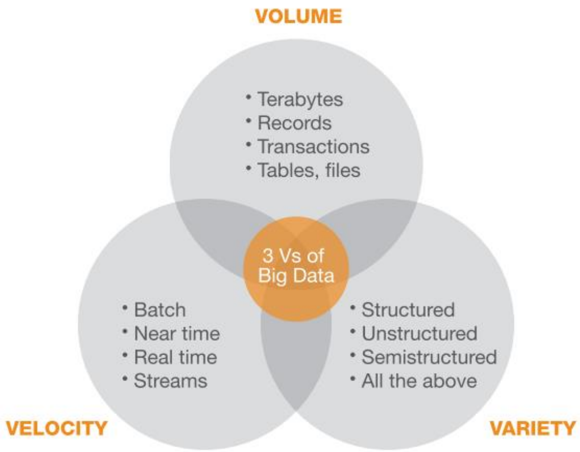
Furthermore, large amounts of valuable Data are being generated and recorded from devices and technologies owned by business and individuals. An individual can for e.g., own a huge amount of data from several devices such as desktop, laptop, smartphone, tablets etcetera. Such types of data with huge volume, variety and velocity, referred to as" Big Data", require new methods and tools to be managed and utilized (Russom, 2011).

2.2.2 Big-Data

Big Data refers to datasets that have become so large and complex (in terabytes and above) that it is difficult to handle in the traditional database management systems (Kubick, 2012). In addition to the 'big size' the primary attribute of big data, variety and velocity are other attributes of big data. According to Russom (2011) variety refers to the wider range of sources and types of data, and Velocity refers to the speed of data creation or data transmission.

Doug Laney is largely regarded as the inventor of the first three Vs of Big Data in 2001. His initial 3vs were based on his mergers and acquisitions experience. The terminology and ideas were simple to grasp and relate to. Since then, the number of Vs has increased (16 additional Vs) (Cartledge, 2016).

Figure 2-1 The three Vs of big data Source (Russom, 2011)



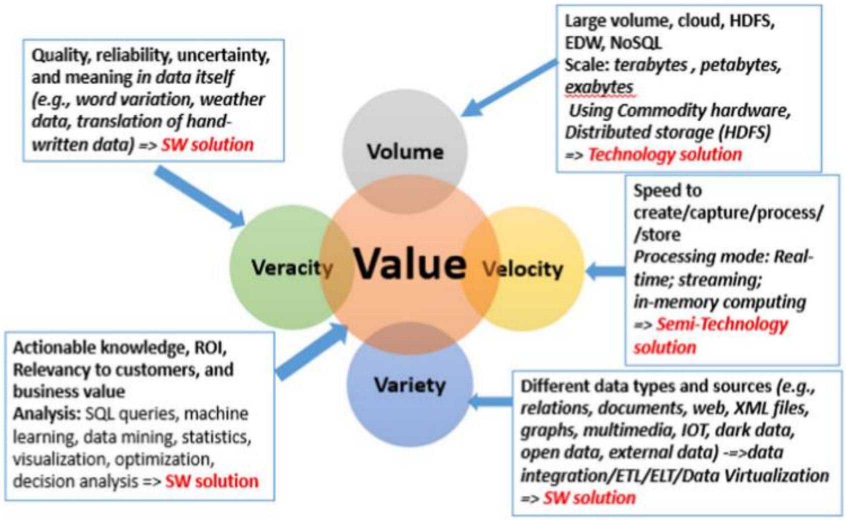
Veracity, as added by IBM which refers to quality of data (Jagadish, 2015). It's associated with reliability, uncertainty, incompleteness, and the meaning in the Data itself (Storey & Song, 2017).Value according to Storey and Song (2017) is measured via identifying "actionable" knowledge and return on investment (ROI) for e.g., as determining value from Big Data can be difficult.

Big data can have a major impact on business and society, and some of these effects are already being felt. For example, Big data technology made the "data-driven paradigm" (analysis and decision making) a reality, making it more sophisticated and automated. However, technologies, such as software and hardware techniques to dealing with big data, as well as approaches to big data analytics employing sophisticated and automated tools, must be understood by computer scientists, conceptual modelers, and management information systems professionals (Storey & Song, 2017).

2.3 Information

When data gets meaning through value-adding activities (aided by technology): contextualization, categorization, calculation, correction, and condensing, it becomes information. And through human intervention via comparison, consequences, connections, and conversation information is converted to knowledge (Davenport & Prusak, 1998)

Figure 2-2 The 5 Vs of Big Data Source: (Storey & Song, 2017)



2.4 Knowledge

Knowledge comprises the information that is put to use and enriched by the decision makers' experience and expertise in addressing and resolving complex problems (Heang & Mohan, 2017). Failure to fully understand what is needed for use by organizations may often determine their success or failure (Davenport & Prusak, 1998).

2.5 Business Intelligence and Analytics and Big Data Analytics

Businesses generate an enormous amount and variety of data daily. Companies need methods and tools to turn their data into actionable insights in order to make better decisions, identify problems, and be profitable (Tableau, 2021).

Data usage for decision-making existed since the beginning of decision making. However, business analytics is a term that was born in the mid-fifties, with the introduction of powerful tools that could produce and collect a greater volume of information and discover patterns in it considerably faster than the unaided human mind could (Davenport, 2013).

companies are now shifting their focus to analytics and are investing in data analytics to understand their customers better, forecast revenue and inventory, and understand rivals, among other things. The investment in data analytics is no longer a "luxury, but rather a requirement for any company that wishes to remain competitive (KMAKI, 2016,p. 14).

2.5.1 Business Intelligence

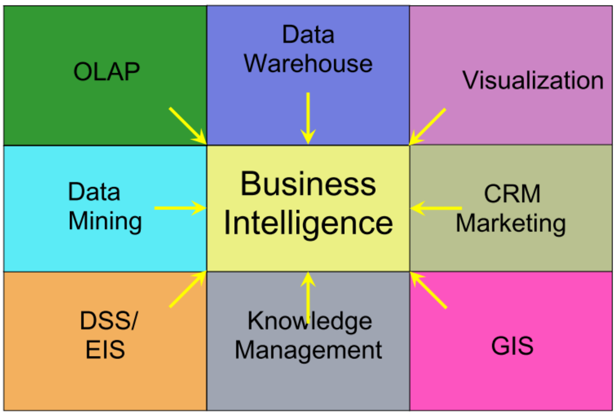
In the early 1970s, Scott-Morton first articulated the essential concepts of DSS (Decision Support Systems), which refers to decision aid tools that are computer-based and interactive for solving unstructured problems via utilizing data and models. In the mid-19050s, advancements in technology and new web-based tools such as OLAP, data warehousing, data mining, and intelligent systems started to appear under the term Business intelligence (BI) and Business Analytics. By 2006, Major commercial products and services appeared under the umbrella term BI which encompassed visualization, alerts, and performance measurement capabilities that the earlier DSS, also known as executive information systems (EIS), could not handle (Sharda et al., 2014.p 13-14).

Howard Dresner (analyst at Gartner Research) was the first to introduce the term Business Intelligence (BI) in 1989 (Power, 2008) to describe "a broad category of software and solutions for gathering, consolidating, analyzing and providing access to data in a way that lets enterprise users make better business decisions." According to Power (2008), a BI is data-driven DSS that primarily facilitates querying of a historical database and the creation of periodic summary reports.

BI progressed from a sequence of preceding decision-support systems. The evolution of the data warehouse as a repository, advancements in data cleansing that lead to a "single source of truth," increased hardware and software capabilities, and the rise of Internet technologies that provided the prevailing user interface have all combined to create a more productive business intelligence environment than previously available. BI collects data from a wide range of systems (Negash, 2004). According to Negash (2004) BI systems convert data to useful information and by applying "human analysis" the information is transformed to knowledge. The goal is to improve decision-making by providing quality inputs to the decision-makers at the right time and, hence improving managerial work. (See Figure 2.4)

BI systems are solutions for converting data into information and knowledge. They also foster an environment in which organizations can make better decisions and strategic thinking and acting (Olszak & Ziemba, 2007). According to the authors, BI technological infrastructure, as shown in Figure 2.5, predominantly incorporates essential components related to key information technologies associated with data acquisition (ETL) together with storing (Data Warehouses), and information technologies particular to all-round data analysis OLAP (On-Line Analytical Processing) along with presentation capabilities (graphic and multimedia interfaces) as listed below.

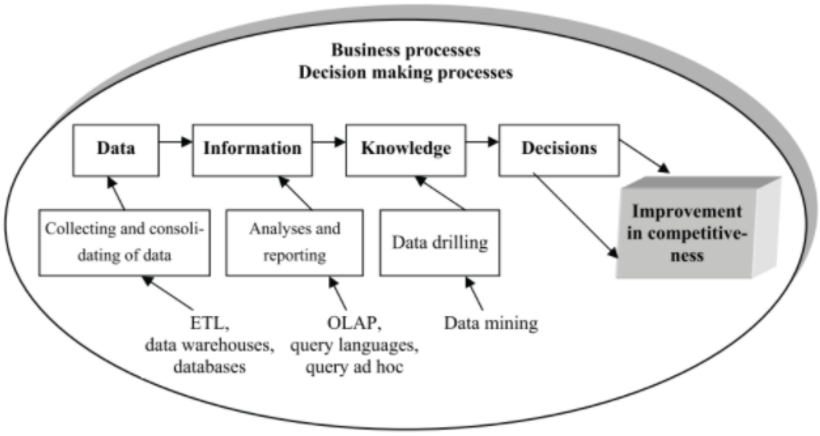
Figure 2-3 BI Relation to Other Information Systems (Negash, 2004)



a) Tools to Extract, Transform and Load Data (ETL, tools)-primarily for data transfer from "transaction systems and the Internet to data warehouses," b) Data Warehouses-provide some space for thematic storage of aggregated and already analyzed data, c) Analytic tools (OLAP)-allow users to access, analyze and model business problems and share the information stored in data warehouses, d)Data mining tools – allow users to discover various patterns, generalizations, regularities, and rules in data resources, e) Reporting and ad hoc inquiring tools –for creating and utilizing different ad hoc reports; and, f) Presentation layer –graphic and multimedia interfaces to access information in a comfortable and handy form.

BI according to Watson and Wixom (2007) is a process with two major activities: "getting data in": and "getting data out". The "getting data in" activity refers to the traditional Data Warehousing that entails transferring data from several sources into a single Data Warehouse. The source systems reflect a variety of technical platforms and data structures. Sources may reside within the organization or may come from external data providers or from a business partner. The importance of a data warehouse is realized when users and applications access the data and use it to make decisions; only then can the Company realize the full value of its data warehouse. As a result, "getting data out" gets the most attention from organizations. The "getting data out" activity, referred to as BI by Watson & Wixom, consists of business users and applications accessing data from the data warehouses for Enterprise reporting, OLAP, Querying and predictive Analytics activities.

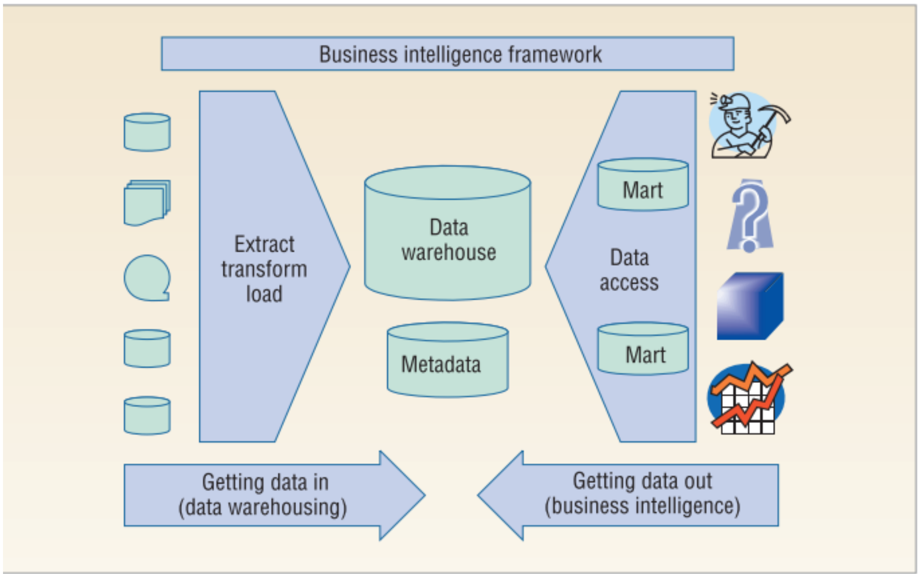
Figure 2-4 The Role of BI Systems in decision Making Source : (Olszak & Ziemba, 2007)



The goal of implementing Business Intelligence in an enterprise is to improve organizational performance. When implementing BI, according to Wixom and Watson (2010, as cited in, Nykänen et al., 2016) is one of the three potential goals. 1) to address well-defined and small problems, 2) to utilize enterprise-wide BI infrastructure and take a comprehensive approach to collecting and analyzing data across the organization, and 3) Using BI to facilitate organizational transformation via business model analysis and restructuring. Revision of the strategies considers those factors affecting the operations obtained from the analysis of the business operation and environment. Thus, according to Nykänen et al. (2016), the organization's goal determines the technology, procedures, and scope of the BI implementation.

Despite the benefits, Watson, and Wixom (2007) argue that success with BI is not spontaneous. For companies to realize the benefits of BI, the authors prescribe considering key factors such as Senior managements' commitment to implement organizational use of BI and must provide the required resources. Management needs to emphasize the use of information-based decision-making. However, according to Watson and Wixom, instilling information, and analytics culture for decision-making from intuition-based practice can be challenging to embrace quickly and require new people to hire. There must also exist a strong BI and Business strategy alignment with effective BI governance. With solid governance addressing an issue like data quality, BI can be a powerful enabler of business strategy. Maintaining a robust data infrastructure needs to be in place if users need to rely on the results obtained from the data analysis. In addition, users should be provided with data access tools appropriate for their needs; they must be trained to use the tools and the available Data or get support from an expert (Data scientist or consultants) to succeed in utilizing BI.

Figure 2-5 Business Intelligence Framework Source : (Watson & Wixom, 2007)



2.5.2 Business Analytics

Business analytics, is a term that has been confused and used interchangeably with BI (CGMA, 2016). Many professionals and academicians now refer to BI as Analytics. Notwithstanding the subtle difference in their definitions, analytics can be conceived of as a method of making actionable decisions or recommendations based on insights acquired from past data. (Sharda et al., 2014).

This view is also in line with CGMA's (2016) view of analytics that refers to the "competencies, Processes, technologies, applications, and practices" involved in generating "insights" from the analysis of data from several perspectives. According to CGMA, the outcome of the analysis, the "insight" provides decision-makers a better understanding of what happened previously and its cause and predicts what may happen in the future or indicates areas of performance improvement (CGMA, 2016).

According to Tableau (2021), the main difference between business intelligence and business analytics is the questions they answer. BI answers the questions "what" and "how" (descriptive focus) to repeat what works and change what does not, and BA answers the question "why" (predictive focus) to create more educated predictions about what will happen. With BA, one can foresee the future and make the required changes to succeed. While data analytics and business analytics are included in BI, they are only used as part of the overall process. Users can derive conclusions from data analysis with the help of BI. Data scientists delve into data details, employing complex statistics and predictive analytics to spot patterns and predict future trends. "Why did this happen, and what could happen next?" data analytics ponders." Business intelligence breaks down the outputs of those models and algorithms into practical language (*Tableau, 2021)*

2.5.3 Types of Analytics

Based on the level analysis employed, the technology involved and the aim/goal of the analysis, Sharda et al (2014,p. 21) describe three types of analytics based on INFORMS (Institute for operations Research and the Management Science) proposal, as summarized below:

I. Descriptive analytics

Descriptive or reporting analytics involves understanding what is going on in the Company and the underlying trends and causes of such events. First and foremost, this entails consolidating data sources and making all essential data available in a format that allows for timely reporting and analysis. *Visualization* is a superior technology that emerged as a vital participant in this field. Organizations can build tremendous insights into their operations using the latest visualization technologies on the market.

II. Predictive analytics

Predictive Analytics aims at determining the probability of events happening in the future based on historical data analysis. It involves statistical techniques and other procedures that fall under the umbrella term, data mining techniques. The purposes of the analytics, for example, include predicting whether a customer is likely to “churn: (switch to a competitor), the likelihood of customers to buy an item and expected purchase amount, customers’ creditworthiness, et cetera.

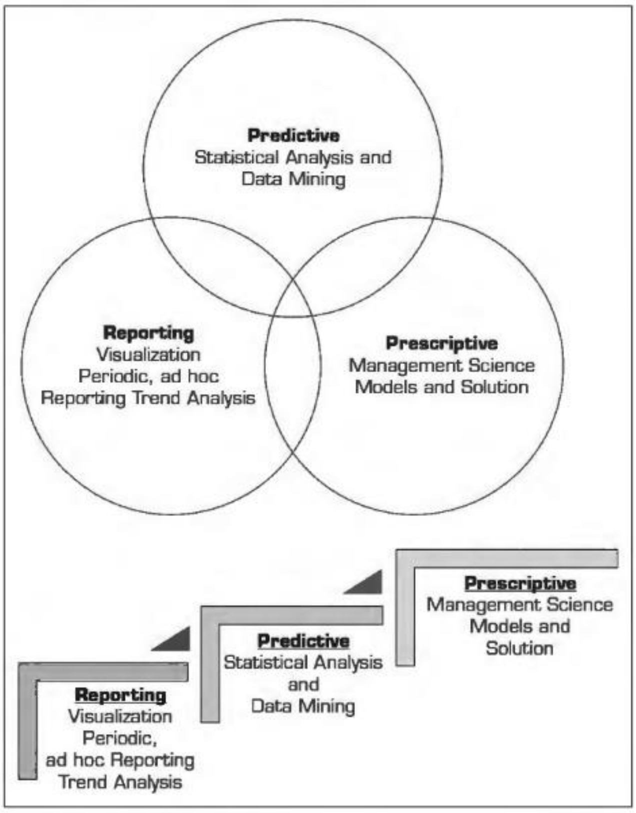
III. Prescriptive analytics

Prescriptive analytics aims to understand what is happening now and what is expected to happen in the future and make decisions to attain the highest results possible. It involves traditional Operations research (OR) or Management science techniques to provide decisions or recommendations for a specific action. These types of analytics are also called decision or normative analytics.

2.6 Big Data Analytics

Big data analytics is the application of advanced analytic techniques to large data sets. According to Russom (2011), big data analytics is about 1) big data and 2) analytics, and how the two have colluded to generate one of the most significant trends in BI today. Without this “perfect duo,” Sanders (2014, p. 7) argues that Big Data remains just “big.” analytics becomes a tool equipped with mathematics and statistics. Because Big Data and analytics supplement each other, the continued use of analytical tools, even the simplest ones, will result in betterment, advancement, and sophistication. And it’s with this combination that insight is converted to information and leading to Business intelligence.

Figure 2-6 Three Types of Analytics Source: (Sharda et al., 2014, p. 20)



Advanced Analytics comprises tools and techniques such as data visualization, artificial intelligence, natural language processing, and database capabilities that support analytics (in addition to the predictive, data mining, statistical and complex SQL) capabilities (Russom, 2011). The main goal of analytics, according to Russom, is "insight discovery," hence recommending the terms "discovery analytics," or "exploratory analytics," as some people already call it. A business analyst would require enormous data (Data not exploited by analytics) with lots of details to apply the "discovery analytics."

Organizations turn to predictive and prescriptive (advanced analytics) with the hope of discovering and capitalizing on new business insights. The transition to an analytics-based organization may necessitate hiring experts with specialized skills. However, more importantly, it demands changing existing employees' mindsets, learning new skills, and embracing new business processes. Changing people's working habits necessitates several elements, including access to correct data, user-friendly data analysis tools, and user training, but it also necessitates cultural shifts. The availability of appropriate data and technology is a necessary but not sufficient prerequisite (Watson, 2016).

In an organization that is adopting analytics and a Data driven culture, should provide employees with the required tools to develop dashboards relevant to their daily tasks, as a first step. Self- Service BI according to Alpar and Schulz (2016, as cited in Berndtsson et al., 2018) allows users to conduct some of their own descriptive analysis. This necessitates user training in tools such as Power BI, Tableau, Watson, and Qlik Sense (BI tools). Next, the capability to conduct predictive analysis via data mining tools such as Azure Machine Learning, RapidMiner, and the programming language R, must be provided. These advanced tools allow organizations to use (semi) automated "insight discoveries or smart data discoveries''. The skills and the logic behind the several algorithms of these tools should be outlined to the users. Even if the tools are technically sophisticated, the aim is for them to be user friendly, such as through "natural language interfaces, visualizations, and recommendations (Berndtsson et al., 2018) Berndtsson et al. emphasize that, in an organization with a data-driven decision-making culture, data surpasses opinions, 'test and learn' (Analytics & insight discovery) is a norm, and failures are tolerated as long as lessons are learned from it.

2.6.1 Data Visualization

Data visualization (DV) is the process of expressing Data graphically or pictorially clearly and effectively. It has developed as a powerful and widely applicable technique for analyzing and understanding big and complicated data sets. It has evolved into a quick and simplistic way of communicating information in a universal format (Sadiku et al., 2016).

DV is an area that draws from a diversity of fields. Psychology (data perception and factors that influence perception), computer science and statistics (Machine Learning & data mining techniques), and Graphical and multimedia designs (integrating multiple forms of media. for e.g., Video games) for building infographics (imagery, charts) and dynamic dashboards. And it is because of these combinations that it has the power to impact how people experience information about their way of life (Aparicio and Costa, 2015).

With charts and graphs, the human brain can process vast and complex information, more easily than common spreadsheets and reports. DV provides the capability to explore several scenarios with slight manipulation/modifications. DV can help identify areas for improvement, interpret factors that influence customer behavior, predict sales volumes, and helps understand which products to place (SaS, 2021)

The most crucial feature of visualization is that it should be interactive (user's engagement with visualization), when "hovering over," visualization should display relevant information, there should be a "zoom in and out" panel, and the visualization should change itself at runtime if a subset or superset data is selected (Ali et al., 2016).

2.6.2 Visualization Tools

Some of the most popular visualization tools include Tableau, Power BI, Plotly, Gephi, Excel 2016, Watson, and Qlik Sense (Ali et al.,2016, Berndtsson et al., 2018). Some of the capabilities in line with the research theme are briefly described.

i. Tableau

Tableau is an interactive (Business Intelligence-focused) data visualization tool. Tableau offers a wide variety of visualization possibilities. It allows users to design their visualization. It is quick and adaptable. It supports almost all data formats and connects to various servers, ranging from Amazon Aurora to Cloudera Hadoop and Salesforce. Its user interface is simple and provides an extensive range of charts. It requires no coding for simple computations and statistics, but models can be run in R and then imported into Tableau for more complex analytics. Based on the task at hand, this necessitates a significant amount of programming expertise. Fig 2.8 shows sample filled map visualization built on Tableau.

ii. Power BI

Power BI, a business analytics service by Microsoft, is a robust business analytics service delivered over the cloud. It comprises three components: Power BI Desktop, Service (SaaS), and Apps. These features make Power BI is both flexible and persuasive. It allows integration from 60 different kinds of sources and visualization can start in minutes. It also combines well-known Microsoft tools such as Office, SharePoint, and SQL Server. It differs from other tools in that it allows users to query the data using “natural language.” Like Tableau, Power BI does not require programming abilities, and one can run scripts on R (Ali et al., 2016)

iii) Excel 2016

Microsoft’s Excel, according to Ali et al. (2016), when combined with visualization techniques such as “Conditional Formatting” and interactive graphs, is a strong contender in the “ocean of Big Data visualization” tools. Excel 2016 is a sophisticated visualization tool as well as a Big Data and statistical analysis tool. Excel Power Query can connect to most services such as HDFS (Apache Hadoop Distributed File System), SaaS (Software as a service), and others and manage semi-structured data.

Selecting the suitable Visualization tools should depend on the business requirements, in agreement with the Company’s budget for investment in such tools. Tableau, for example, tends to be highly expensive for small companies. According to Ali et al. (2016), if the tools integrate with popular data sources (like MapR Hadoop), the level of visual interaction, the availability of tutorial or online learning (MOOCS), the intensity of interactive Visualization, Client Types (if Desktop, online, or Mobile App is available), and the availability of API to embed the services of the tools are key attributes to consider. All these should be done in consideration of internal resource type and the visualization tools i.e., if Open source or not.

Chapter 3 **RESEARCH METHODOLOGY**

3.1 Introduction

This section introduces the methodology followed for the research project. It briefly describes the research approach, research process, research design, data collection, and analysis conducted to realize the general objective of the research project. The reliability and validity, and ethical considerations are described at the end of the chapter.

3.2 Research Process

The research Process comprises steps essential to effectively carry out the research and the specified development of these steps (Kothari, 2018, P. 10). The researcher first defined the problem/opportunity, next conducted an extensive literature review on the subject matter to get an understanding of what is known, then the research's general and specific objectives, research questions, and scope of the research were formulated, after that, the research approach and design were identified, methods of data collection and analysis were selected, and finally, the results were interpreted and presented

3.2.1 Research Approach

When planning to conduct a research project, one must identify the type of research design to employ. Based on the combination of worldview or set of assumptions about the research, specific inquiry strategy, and research methods, research is categorized as qualitative, quantitative, or mixed methods. Factors such as the study problem or subject being investigated, the researcher's personal experiences, and the audience for whom the researcher writes all influence decisions (Creswell, 2009,p. 20). According to Creswell, qualitative research investigates and understands the significance that individuals or groups attach to a social or human issue. Emerging questions and techniques are part of the research process. Typically, Data is gathered in the participant's environment. Inductive data analysis builds from specifics to broad ideas and the researcher's perceptions of the Data's meaning. The final written report's composition is flexible. In contrast, quantitative research examines the relationship between variables to test objective theories. These variables can then be measured using tools, resulting in numerical data that can be examined using statistical processes. Introduction, literature and theory, methodology, results, and comments are included in the final written report. Finally, in mixed-methods approach to research integrates or associates both qualitative and quantitative modes of inquiry. It entails philosophical assumptions, the application of qualitative and quantitative methods, and the combination of the two in a study. A mixed-methods approach to research integrates or associates both qualitative and quantitative modes of inquiry. It entails philosophical assumptions, the application of qualitative and quantitative methods, and the combination of the two in a study. As a result, it entails more than just gathering and evaluating both types of data; it also entails combining the two approaches so that the overall strength is more vigorous than either qualitative or quantitative research. Therefore, given the research objective and addressing the research questions, which utilizes concepts of statistical and techniques, a quantitative approach is selected for the study.

3.2.2 Research design

A research design, according to Yin (2003) is a "blueprint" for research. It addresses at least four subjects: what questions to study, what data are relevant, what data to gather, and how to analyze the results. The purpose of a Research Design is to gather relevant evidence with the least amount of effort, time, and money possible. However, all of this can be achieved depending mainly on the research goal (Kothari, 2018, P. 14). According to the author, based on the purpose of the research, four categories of designs are identified, i.e., Exploration, Description, Diagnosis, and Experimentation. If the objective of the research study is to explore, a flexible research design that allows for the consideration of many distinct facets of an issue is regarded as appropriate. However, when the goal is to describe a scenario or a relationship between variables accurately, then the best design minimizes bias and increases the dependability of the data collected and analyzed.

Descriptive research is a reliable option when the study aims to find traits, frequencies, trends, and classifications. It is advantageous when there is not much information on a topic or problem. Before you can investigate why anything occurs, you must first comprehend how, when, and where it occurs(Creswell, 2009, p. 137) Because these questions are answered by a descriptive research design and in line with the research objective a descriptive research design was adopted for this study.

3.2.3 Research Methods

Research methods refer to all the procedures employed by the researcher while investigating his research problem. It is concerned with methods for data collecting, statistical techniques for building connections between data and unknowns, and methods for evaluating the precision of the results obtained (Kothari, 2004, p. 8)

3.2.4 Case Study Method

To fully address and conduct the research project's objective, i.e., is to examine Export, Import and DnD Datasets using an advanced Data visualization technique and tool to extract meaning and insights and to describe the results, a case study method was chosen. Case studies are employed when a detailed understanding of a particular problem or phenomenon is sought (Patton,1987 as cited in Noor, 2008). "It is a method of study in depth rather than breadth(Kothari, 2004, p. 113)

A single case study was employed to perform an in-depth investigation of the study. When selecting the case, three selection criteria were considered: 1) to select a case where DDDM concepts can be applied 2) to select a case where huge datasets can be found to perform advanced analysis to discover insights 3) to select specific areas in the case company to apply data analysis.

The Datasets were collected from the case company based on criteria 2 and 3 above. To perform data analysis on a larger dataset, the researcher set a time frame of 11 years, i.e., from the year 2010 to 2020. WEBI, a business intelligence tool of the case company, was utilized to gather the data.

3.3 Data collection

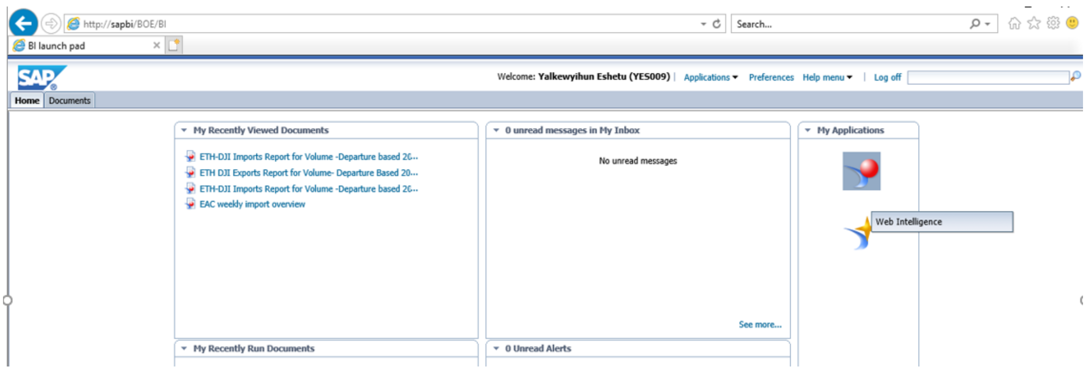
3.3.1 Dataset for Import and Export Shipments - 2010-2020

As indicated in the specific objective of the research, the first step taken was to gather the required data. A secondary source of data for Import and Export shipments was collected for the years 2010 to 2020 using WEBI, the SAP BI tool of the case company.

A report was pulled from SAP Business Objects Web Intelligence (WEBI). SAP BI is the most utilized BI tool in the organization, with over 5000 users connecting to over 60 universes (Semantic layer-designer) and over 30 data sources. The data sources used consist of several Business Intelligence data warehouses and real-time replicas of key source applications as well as a direct connection to SAP Business Warehouse (BW). SAP Business Warehouse (BW) integrates, transforms, and consolidates relevant business information from productive SAP applications (Maersk BI Portal, 2021).

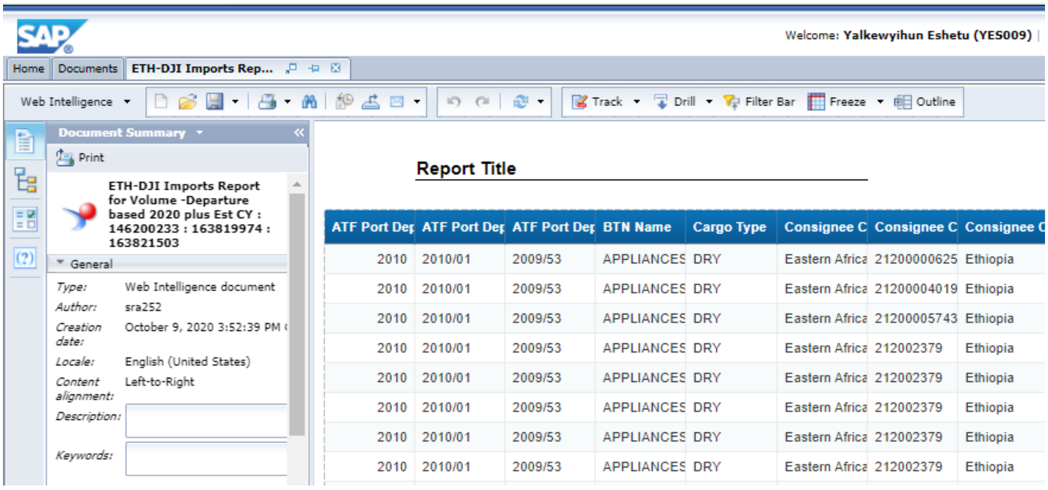
The researcher ran the query that was already designed by a business analysis of the case company (based on the "Shipment Summary" tab on GCSS (Global Customer Service System) that handles the end-to-end shipping process through various interfaces and external applications. Figure 3.2 shows the report pulled after a query was run based on the parameters set.

Figure 3-1 SAP Business Objects BI-Web Intelligence-launch Pad



The "Shipment Summary" details include information such as Shipment Number, Customer commodity, Business Unit, Place of Receipt (Load Port), Place of Delivery (Discharge Port), Type of Cargo, Container Size, Container Type, Container Number, weight, Vessel/Voyage Number, Freight Amount (to name few). The overview of the summary is shown in Appendix 1. The report pulled was then extracted to MS Excel for further analysis (See Fig.3.2)

Figure 3-2 SAP BI-Web Intelligence-Report View



3.3.2 Data pre-processing

The Data was then pre-processed using Microsoft Excel 2016 before further analysis. The pre-processing activities were:

1) ***Filtering shipment for Ethiopia Area***: Because Load Port and Discharge Port for Ethiopia and Djibouti Business Units is the port of Djibouti, it was essential to identify the exact shipment for Ethiopia Business unit that was shipped(transported) by the case company for the mentioned years. "Consignee customer code" was used as a base to filter for all import shipments, and "Shipper customer code" was used to identify export shipments. The unique code that identifies all Ethiopian customers starts with the prefix 212xxxxxx, and that of Djibouti starts with the prefix 213xxxxxx. Table 3.1 summarizes the filtered values of the dataset.

Table 3-1 Summary of the initial SAP BI-Web Intelligence-Report converted to MS excel

Year 2010-2020	Number of Rows	Number of Columns	Load/discharge Port
Import	223,568	48	Djibouti
Export	53,104	48	Djibouti

2) *Column header/value cleanup:* The second step was to review the columns headings to see if the accurate and logical naming was placed and also to see if the columns had the correct format (if Number and text combined, repeated details) in the column representing a single value for the specified item. As can be seen from Figure 3.3, columns had unclear naming, and year values were repeated in the month and weeks column. The right hand of the tables shows the transformed headings**.**

Figure 3-3 Initial and transformed headers and column values

Initial coloums Heading and value				Transformed Heading and Value			
ATF Port Dep 1 Year	**ATF Port Dep 1 Yr/Month**	**ATF Port Dep 1 Yr/Week**	**BTN Name**	**Year**	**Month**	**Week**	**Commodity Group Name**
2010	2010/01	2009/53	APPLIANCES	2010	1	53	APPLIANCES
2010	2010/01	2009/53	APPLIANCES	2010	1	53	APPLIANCES
2010	2010/01	2009/53	APPLIANCES	2010	1	53	APPLIANCES

3) Column Selection: Because all consignees (Import) and shippers (Export) details are not equally important for decision making and some of the column values represent similar values with little or no value for insight discovery, they were excluded from further analysis. The researcher carefully evaluated each columns' contents and consulted the Company's product and sales consulting teams to identify the most important decision-making factors.

Therefore, based on contribution to insight discovery criterion set by the researcher, the columns were reduced to 21. See table 3.2. The whole (48) column detail is found in Appendix 2

Table 3-2 Summary of the filtered Ethiopia Import and export shipments (Own elaboration)

Year 2010-2020	Number of Rows	Number of Columns	Filtering criteria
Import	165,844	21	Consignee customer code-212xxxxx
Export	46,880	21	Shipper customer code- 212xxxxx

4) Dealing with null values: The final step was to check for null values. Based on the analysis, null values were in the numerical measures columns, Basic Freight(currency), Cont. Yield (currency), Net Freight(currency), FFE (Count), and TON (Weight).

Table 3-3 Summary of the null and Zero values

Activity	Description	Basic Freight	Cont. Yield	Net Freight	FFE	TON
IMPORT	Empty-Values	136	136	136	0	30
	Zero Values - Count	38	994	2	30	250
	Negative Values-Count	3402	2517	8	-	-
	Sum of the Negative values	$ (3,362,108.89)	$ (1,329,151.78)	$ (29,345.51)	-	-
EXPORT	Empty-Values	28	-	28	-	-
	Zero Values - Count	31	143	5	65	54
	Negative Values-Count	62	196	2	-	-
	Sum of the Negative values	$ (25,769.00)	$ (136,121.50)	$ (221.25)	-	-

Source: Own Elaboration

To increase the reliability of the measures, basic freight was excluded from the analysis, making the total number of columns in both import and export datasets Twenty in total. Because the null values for CYield, Net freight, and the number of containers (FFE) will not have a significant impact on the overall analysis compared to the size of the datasets they were included. Negative values for CYield can be interpreted as a loss-making cargo. However, negative net freight rates (even though minimum) are unusual and had to be managed in tableau analysis with caution.

5) Final step- the cleaned datasets were linked to Tableau for further analysis.

3.3.3 Dataset for Demurrage and Detention (DnD) - 2016-2020

DnD dataset was extracted for the year 2016 to 2020 from CXED (Calculation Easy at Demurrage). Extraction criterion was “discharge date” prior 2021: The Date the container was discharged at the port of Djibouti and the detention free days starts. Data for prior years couldn’t be extracted from CXED due to mainly the system’s retrieving capacity. The IT team was requested to provide the details; however, considering the time constraint, i.e., the time it takes to obtain the data from the archive (scripts/codes to be written) in line with the project’s timeline, it was decided to proceed with the available Data. The whole point of the analysis was to analyze available datasets to extract meaningful insights.

Figure 3-4 CXED report request Page: Source Own Elaboration

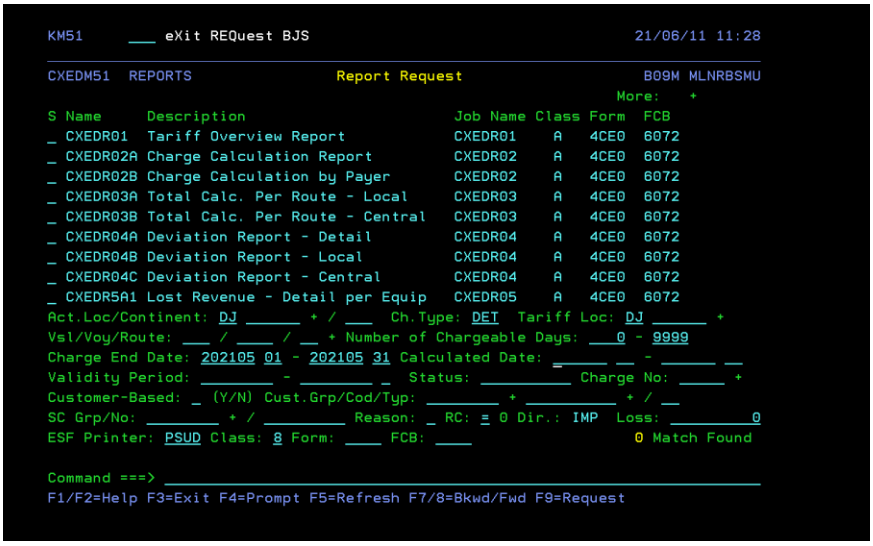


Table 3-4 Summary of the initial CXED report converted to MS excel

Year 2016-2020	Number of Rows	Number of Columns	Discharge Port
DnD- Import Shipments	343,079	17	Djibouti

The extracted data, which was originally in text format. (.txt) and contained: Vessel/Voyage Number, Brand, Transport Document (Shipment Number), Line (Carrier), Consignee Code, Consignee Name, Equipment Id (Container Number), Equipment Type (Container Type), Date & time (Container was collected by customer), Date & Time (The Date & time Free time ends), Date & Time (the container was returned). The text file was then converted to Excel for further pre-processing. The procedures applied were like the Shipment datasets extracting and pre-processing techniques. The procedures briefly included:

Table 3-5 DnD initial extracted report text format

```
CXEDR02A (003).TXT - Notepad
File  Edit  Format  View  Help
CXEDR02A                                                   Easy@Demurrage
                                                  Detention  Calculation Report - IMPORT
Request Criteria: Act.Location=DJ      , Charge Type=DET, Direction=IMP, End Date=20210501-20210531, Calculation Date=       -
                  RC==, Charge Complete=Y

DJJIBT1                                                                Equip. +----FT Start----+ +-----Expiry-----+ +-Ch End-+
Vsl/Voy  T/P No    Line Consignee                              Equip Id.  Type   Date       Time   Date       Time   Date
________ _________ __   _____________________________________ __________ _____  _________  ______ _________  ______ _________
G9X/020W 597891204 Z3   ET002379   ETHIOPIAN SHIPPING & LOGISTIC S/E MSKU2906793 20DRY  20/05/19   00:00  20/06/17   00:00  21/05/15
H7T/111E SSZ732246 Z1   DJ00001263 GLACIERES COUBECHE SARL         MNBU0134615 40HR   21/05/01   00:00  21/05/10   00:00  21/05/10
H7T/111E SSZ732246 Z1   DJ00001263 GLACIERES COUBECHE SARL         MNBU4067027 40HR   21/05/01   00:00  21/05/10   00:00  21/05/11
H7T/111E SSZ732309 Z1   DJ00001263 GLACIERES COUBECHE SARL         MNBU3693509 40HR   21/05/01   00:00  21/05/10   00:00  21/05/05
H7T/111E SSZ732406 Z1   DJ00001263 GLACIERES COUBECHE SARL         SUDU6162604 40HR   21/05/01   00:00  21/05/10   00:00  21/05/16
H7T/111E 1KT077020 Z4   DJ00067105 ELMI GOUMANE ABSIEH-BOULANGERIE D HASU1109610 20DRY  21/05/01   00:00  21/05/18   00:00  21/05/10
H7T/111E 1KT077020 Z4   DJ00067105 ELMI GOUMANE ABSIEH-BOULANGERIE D HASU1160334 20DRY  21/05/01   00:00  21/05/18   00:00  21/05/10
```

(Source: own Elaboration)

1)*Filtering DnD for Ethiopia Area*: for the same reason that Ethiopia and Djibouti use port Djibouti, it was mandatory to filter for Ethiopia DnD datasets. The filtering criterion was "Consignee code." Consignee code for Ethiopia starts with the prefix ETxxxxxx. And the prefix for DJxxxxxx

Table 3-6 Summary of the filtered DnD import shipments (Own Elaboration)

Year 2016-2020	Number of Rows	Number of Columns	Discharge Port
DnD- Import Shipments	248,352	17	Djibouti

2) Column header/value cleanup: The DnD datasets had similar column header issues. And because the dataset didn't have a separate column to show "Year, month and day", an Excel formula YEAR (Cell reference), MONTH (Cell reference), DAY (Cell reference) was used to extract them in a separate column. The datasets contained containers returned in the year 2021 but discharged prior 2021. The reason behind including these items is related to calculating the number of days it took between discharge dates (year <=2020) and return dates (Year=2021).

Table 3-7 Initial and transformed headers and column values

Initial Header		Transformed Headers					
Equip. Type	**Discharge Date**	**Equip. Type**	**Equip. Size**	**Discharge Date**	**Year**	**Month**	**Day**
20DRY	04/18/16	20	DRY	18-Apr-16	2016	4	18
20DRY	04/18/16	20	DRY	18-Apr-16	2016	4	18
20DRY	04/18/16	20	DRY	18-Apr-16	2016	4	18
20DRY	04/18/16	20	DRY	18-Apr-16	2016	4	18

Source: (Own Elaboration)

3) Column Selection: Based on importance for insight discovery and decision-making criteria set for the export and import shipment, the DnD Dataset columns were reduced. With the four columns added to separately show the columns Year, month, date, and container size and six column reductions, the final dataset containing the reduced columns was 15 in total. (See table 3.6**)**. The whole (17) columns detail is found in APPENDIX **3**

Table 3-8 Summary of added and reduced DnD import shipments column

source :(Own Elaboration)

Year 2016-2020	Number of Rows	Number of Columns	Discharge Port
DnD- Import Shipments	248,352	15	Djibouti

4) Dealing with null values: Two columns with "time" attributes were deleted in the prior step as they continued to have null or Zero value and had no relevance.

5) Final step- the cleaned datasets were linked with Tableau for further analysis.

Table 3-9 Reduced columns for Import and Export Datasets

Column-Import/Export	Description
ATF Port Dep 1 Year	Year
ATF Port Dep 1 Yr/Month	Month
ATF Port Dep 1 Yr/Week	week
Consignee Cust Code/Shipper Cust Code	the code that identifies the consignee(import) and the shipper(export) customer
Consignee Cust Name/Shipper Cust Name	name of the consignee(import) and the shipper(export) customer
Shipment Number	a unique number identifying the cargo shipped
BTN Name	commodity group name- e.g., Textile and apparel (Export), Vehicle (for Import)
Item Name	Specific item of the commodity- Wool, animal hair, textiles (Export) Vehicles, cars, buses, trucks, (Import)
Cargo Type	dry or Reefer (A refrigerated Container-cargo)
Container Size	size of the container
POR City Name	port the shipment was received (Load port)

POD Country Name	place of delivery country name -port where cargo is unloaded from the vessel
POD City Name	place of delivery city name -port where cargo is unloaded from the vessel
Shipment Operator	Company/Brands MLL (Maersk Line Limited), MSL (Maersk Line), SCL (Safmarine Line)
Route	The course or direction that a shipment moves - e.g. Far East - Horn of Africa (Z1)
Consignee Sales Control/Shipper Sales Control	customers who make the decision or influence the decision to ship with Maersk Line. (Y) for yes and (N) for No
Est Basic Freight	estimate of the price paid to the carrier for the transportation of goods or merchandise by sea from one place to another
Est CYIELD	estimate of contribution Margin of a shipment plus/minus Flow Adjustment (to account for container positioning costs).
Est Net Frt	Estimated Net Freight - cf Basic freight
FFE	Forty Feet Equivalent- the size of a container-total number
TON	Tonnage- Weight of the cargo measured in ton

Table 3-10 Reduced columns for DnD Import Dataset (Own Elaboration)

Columns Reduced-DnD (Import)	Description
Year	year of Container discharge started
Month	month
Day	day
T/P No	a unique number identifying the cargo shipped
Line	The course or direction that a shipment moves - e.g., Far East - Horn of Africa (Z1)
Consignee	The individual or firm specified on the Bill of Lading and legally authorized to receive the shipped goods
Consignee Name	Name of the consignee
Equip Id.	The number that identifies the container ("Boxes"
Con Size	Size of the container,20 Feet, $0 Feet
Equip. Type	dry or Reefer (A refrigerated Container-cargo)
FT Start Date	Discharge Date- Free time starts to count
Expiry date	time free time ends
Ch End	calculation date- date DnD was calculated
# of days	Number of days from discharge date to return date
Amount (USD)	Revenue calculated (Rate x number of days)

3.4 Data Analysis

Once the datasets got pre-processed, the analysis was performed using Tableau. The tableau desktop workflow/ steps conducted is divided into four steps:1) Connect: -Creating Data Sources & connections to link Tableau to source data/datasets 2) Prepare: -Cleaning Rows and Columns, filtering data, combining different tables & creating calculated fields,3) Analyze & visualize: - Creating visuals to obtain valuable insights from the datasets4), Dashboard & stories: -creating interactive dashboards to visualize the results. Tableau has a state-of-the-art visual interface, statistical capabilities, advanced analytics, computations, and intelligent search capabilities, making it one of the best analytical tools available. Once the dataset was transformed, into the “data source page,” using the drag and drop feature in the “analytics tab” and employing several bar charts, bar graphs, scatter plot, bubble charts, area charts, and trend lines, the visual analysis was performed. Other than simple mathematical models for quantifying totals, averages, frequencies, and ratio analysis performed by the researcher, no significant statistical techniques were explicitly applied.

3.5 Reliability and Validity

When conducting a case study, according to Yin (2003), the quality of the research can be examined from four logical tests: Construct Validity, Internal Validity (for explanatory study only), External Validity, and Reliability. According to the author:

Construct validity refers to establishing the correct measures for the concept of the study. According to Yin, this test is very challenging in case study research. People who criticize case studies time and again point out that the researcher fails to develop a suitably operational set of measures and the data is collected using a "subjective" view. The construct validity of a case study can be increased by showing utilization of different sources of evidence to encourage connecting lines of investigation, which helps gather data. It relates to selecting the specific type of measures related to the research objective and making sure a chain of evidence backs the correct measures is established. A second strategy is to create a chain of evidence, which is also essential during data collection. A third strategy, according to Yin, is to have the draft case study report reviewed by key informants.

To ensure Construct Validity, the researcher reviewed and documented various literature regarding Big data and advanced analytics and the concept and techniques of data visualizations. Based on the concepts, a large dataset from Export, Import, and DnD datasets was collected. The researcher showed that the data collection base was the 'Shipment summary' details found from GCSS, and based on the details, the report was pulled from WEBI. Detailed descriptions of the base for collecting the data and the steps performed to gather data were shown. The researcher measured the number of columns, rows, reasons, and criteria to reduce the columns and exclude some of the columns in detail. Several formal and informal discussions were held with the Sales consulting team and Finance Analyst team. Notes were taken, and essential factors for analytics and decision-making were selected. The construct validity for this study was addressed by showing a chain of evidence in the literature review and data collection stages.

Internal Validity: applied to casual or explanatory case study, refers to the measures where an event x led to an event y. It is to see if the correct relations occur between variables under investigation. Since there were no variable comparisons in the study (cause and effect relationships), and a descriptive case study design was chosen, this test of Validity was not addressed. According to Yin (2013), ***external Validity*** refers to ascertaining the domain to which a study's findings are often generalized. It is about making sure if the study results can be generalized beyond the immediate case study. Because the research output cannot be measured using statistical tools and techniques, *"statistical generalization"* (as in survey research) cannot be made. However, examining Export, Import, and DnD datasets using data visualization, can be verified in other countries in EAA by replicating the research design. The research process, and design was thoroughly documented to address the external validity of the study.

Reliability refers to showing that the procedures of a study, such as the data collection techniques, can be replicated with the same results. The purpose is to be sure that if a later investigator precisely followed the procedures of the previous investigator, they would arrive at the same finding and conclusion. The purpose of reliability is to lessen the flaws and prejudices in a study. One prerequisite for allowing this is that for another investigator to repeat an earlier case study is to document the earlier case techniques (Yin, 2003). The researcher demonstrated the steps and procedures explicitly to make sure the procedures are replicable.

3.6 Ethical Considerations

The researcher was reserved from presenting the name of the customers and their details. Instead, the customers' identification codes were used to identify and describe their activities.

Chapter 4 **RESULTS AND DISCUSSION**

4.1 Introduction

This chapter discusses the visual analytics performed in Tableau on Import, export, and DnD datasets along with the results obtained.

As stated in the general objective, the aim was to examine Export, Import and DnD Datasets using an advanced Data visualization technique and tool to extract meaning and insights and to describe the results. A BI tool that has advanced data visualization and analytics, Tableau Desktop, was used for the study. The Visual analytics process and the marked insights are described in the chapter.

Tableau Desktop is a power BI tool specialized in data analysis and visualization. Analytics in Tableau comprises four activities: *Connect*, *Prepare*, *Analyze* and *Visualize,* and finally *Dashboards* and *stories*. It starts from connecting and preparing and getting ready the datasets. Once the datasets are in the correct format the visuals analytics follows. At this stage, using the various visualizing charts the research questions were answered and explained. Each steps of the analysis and the results of the Research Questions (RQ) are presented as follows.

4.2 Connect

Tableau Desktop is a powerful tool that allows data analysis and data visualization. The first step in Tableau is to connect to the data source. In this step, data is gathered from several sources and that may come in a different format. For this research projects all the datasets were in MS excel format and in a Folder.

4.3 Prepare

By connecting to the data source first, an analyst starts cleaning the data or making sure the proper values of each column are matched. Therefore, the Import, Export, and DnD datasets were connected that were in excel format and were prepared and ‘cleaned’ at this stage.

4.4 Visualize and Analyze

Once all the required datasets are connected and prepared, the next step is to visualize and analyze the data. In *Tableau* the data is organized in two forms: in *Dimensions* and *Measures*. Dimension fields are those fields that get measured and the measures have the quantifiers. For e.g. FFE –a *Measure* and Shippers Code, shipment Numbers as a *dimension.* By dragging and dropping the *measures* and *dimension* in the *Drop fields* and or the *columns* and *rows*. Choosing the appropriate chart types from *Marks Fields*, the analysis and visualization step and answering the research questions was conducted. Figure 4.1 illustrates a new worksheet to perform the analytics and Figure 4.2 illustrates the analytics tab where additional analytics options are available.

Figure 4-1 Tableau Worksheet-Data Tab

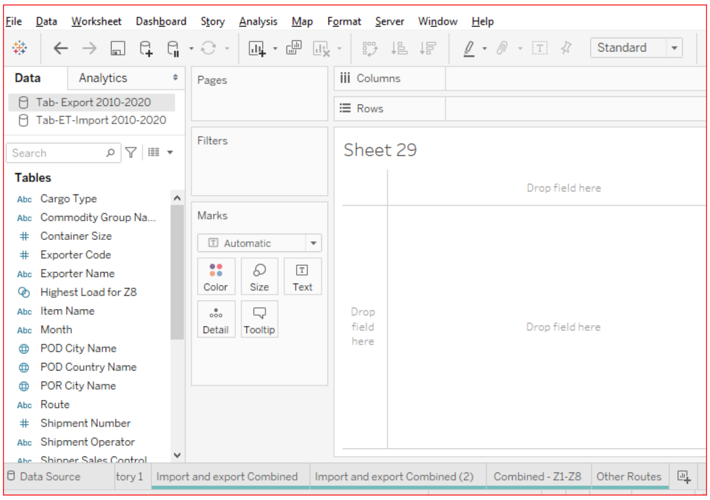
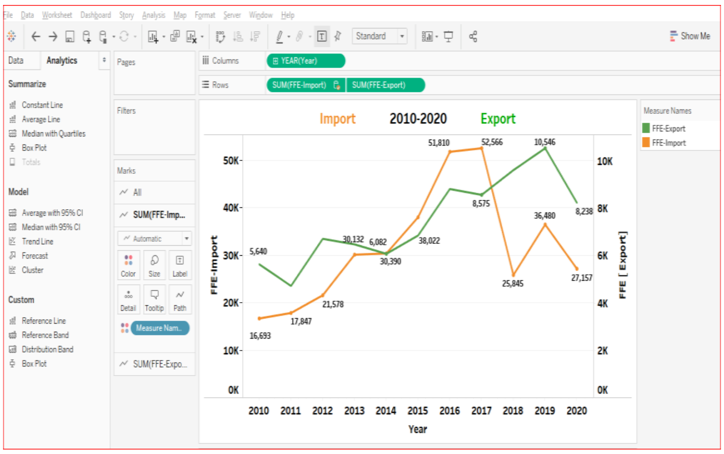


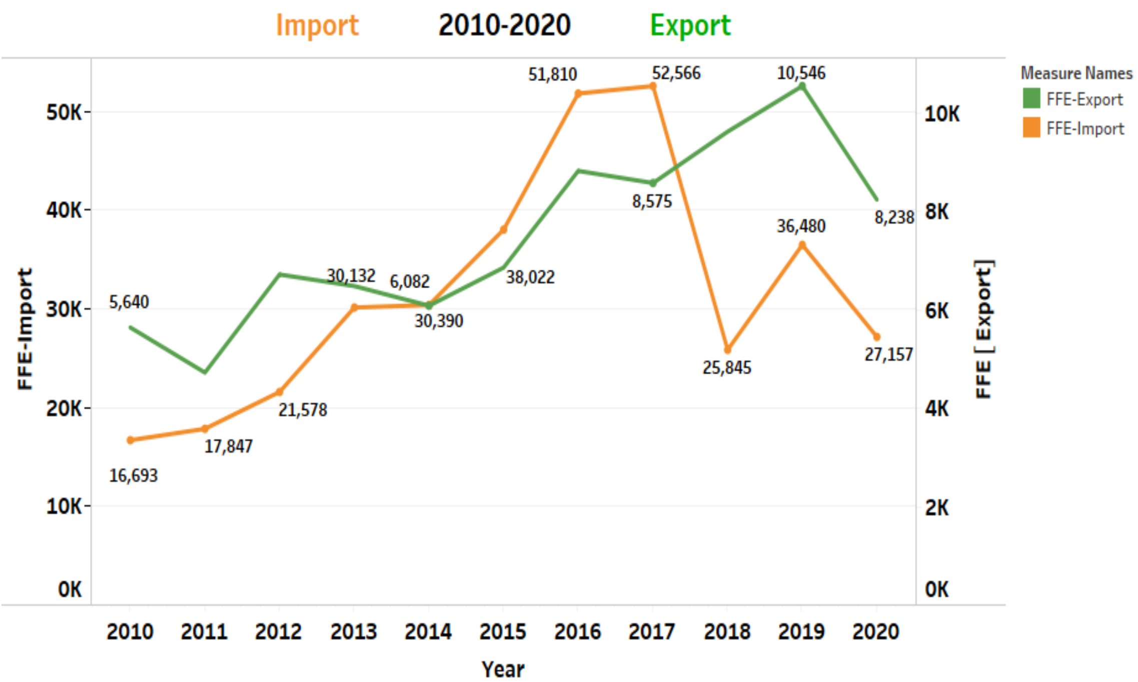
Figure 4-2 Analytics Tab



4.4.1 RQ-1 What is the volume (FFE) trend for Import and Export shipments per Trade for the year 2010- 2020?

Before diving into the Trade performance, a brief look at the overall Import and Export volume, displayed a decline towards the end of 2019. However, 2017 showed the highest import load in the last 11 years; in contrast, it was in the year 2019 that the export load was the highest. Thus, over the years the gap between imports and export remained almost steady.

Figure 4-3 Import and Export Volume Trend (2010-2020)

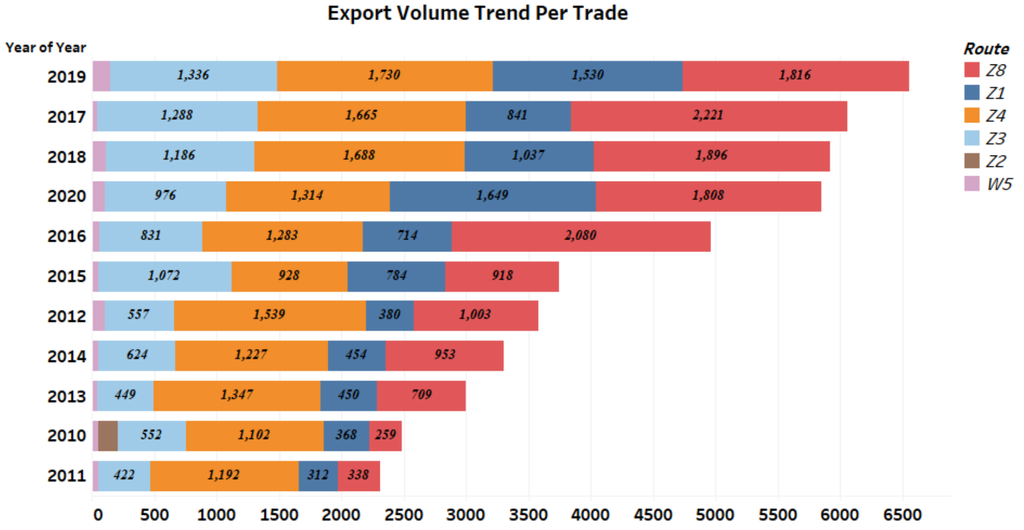


Source: Lines chart Extract from Tableau- Color showing FFE movement

Export volume per Trade

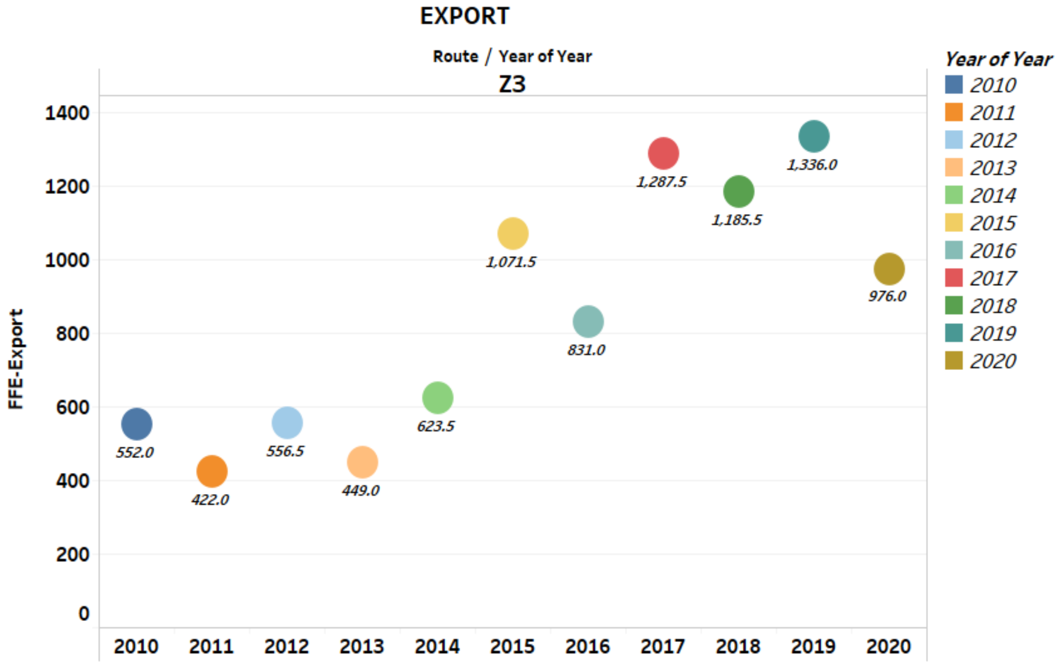
Export shipment volume per trade showed strong performance for Z8 (Far East-HOA) over the years, followed by Z1(Americas- East Africa). Z8 and Z4, except for 2015, had a stable performance loading over 1K FFEs over the years. On the other hand, Intra Africa (W5) trade, despite the low volume movement, showed an increasing trend.

Figure 4-4 Export Shipment Trend - per FFE(Volume)



A peculiar volume movement was noticed for Z3 (Middle east- East Africa), where volume increased one year and decreased right the following year. Looking at the trade trends, one can get tempted to predict that the volume for 2021 will be higher than the 2020 actual.

Figure 4-5 Trade Z3- Volume Trend



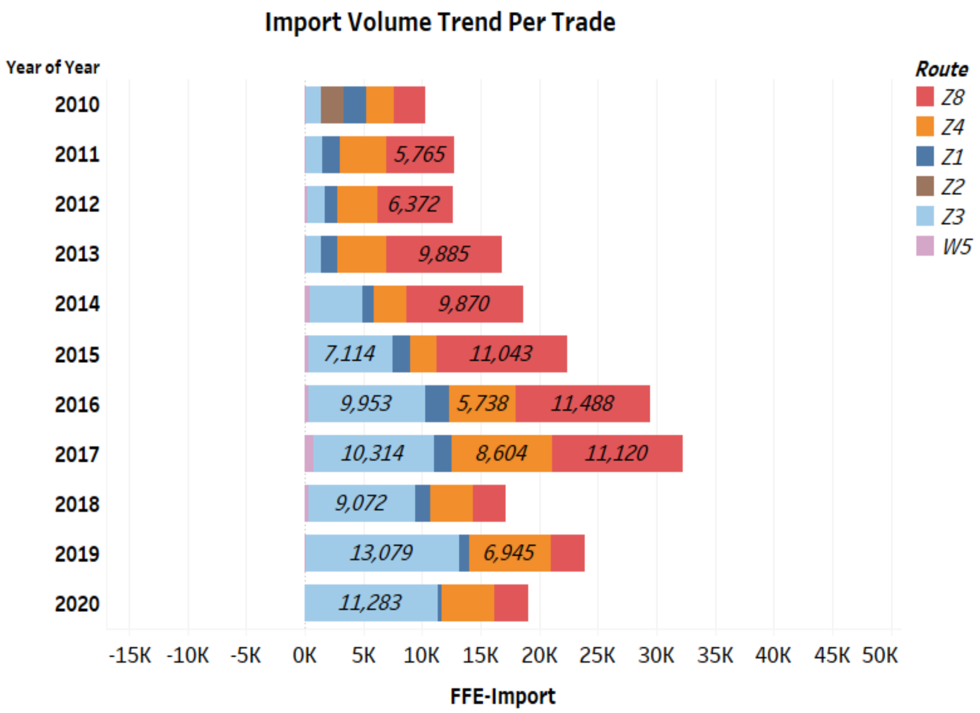
Sum of FFE-Export for each Year Year broken down by Route. Color shows details about Year Year. The view is filtered on Route, which keeps Z3.

IMPORT volume Per Trade

Like export, Z8 volume remained firm for the imports with an average load close to 10K from 2013 to 2017. While Z1 had a significantly reduced volume movement, unlike the export, Z3 volume performance has been on the average increasing since 2014. The peculiar volume movement witnessed in the export could be seen here.

However, it was not as consistent as it was in the export. The highest volume load came from the same trade to the tune of 13k in 2019. The "circle view" chart summarized the trade volume performance over the years. (see figure 4-7). W5 and Z2 (Far East- East Africa) trade had little significance compared to others. Z4 remained a stable trade over the years but with a slight drop in volume in 2018 since 2015.

Figure 4-6 Import Volume per Trade

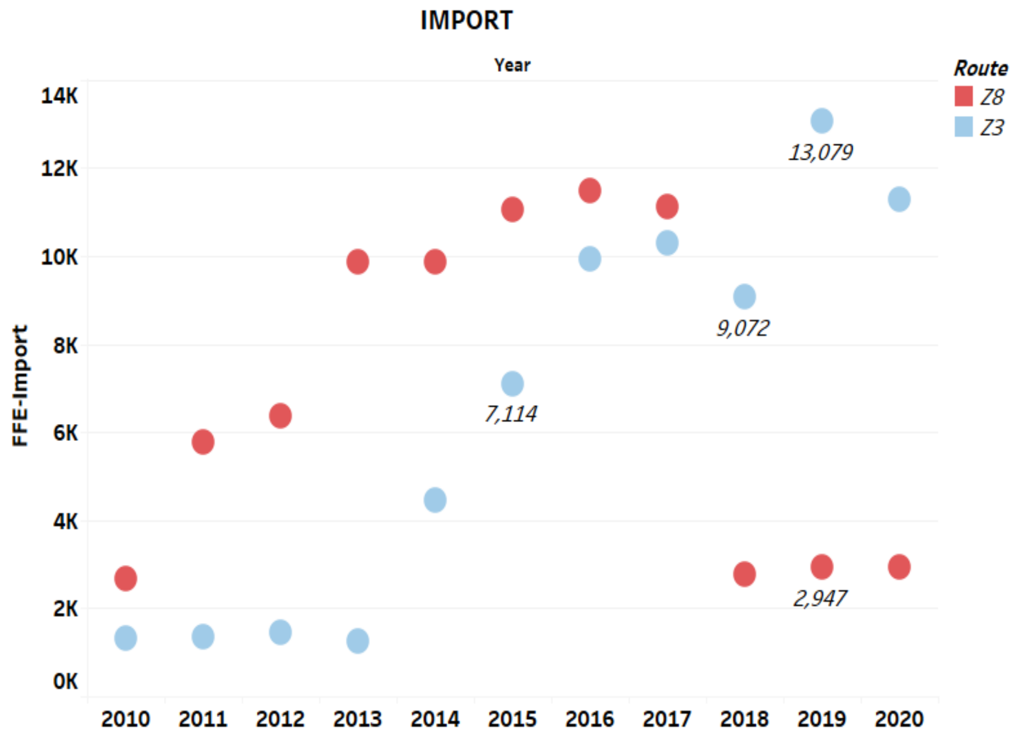


Source: Lines Chart Extract from Tableau – (Own Elaboration)

4.4.2 RQ 2- **What commodities have a higher contribution yield for Import and Export per Trade for the year 2010- 20202?**

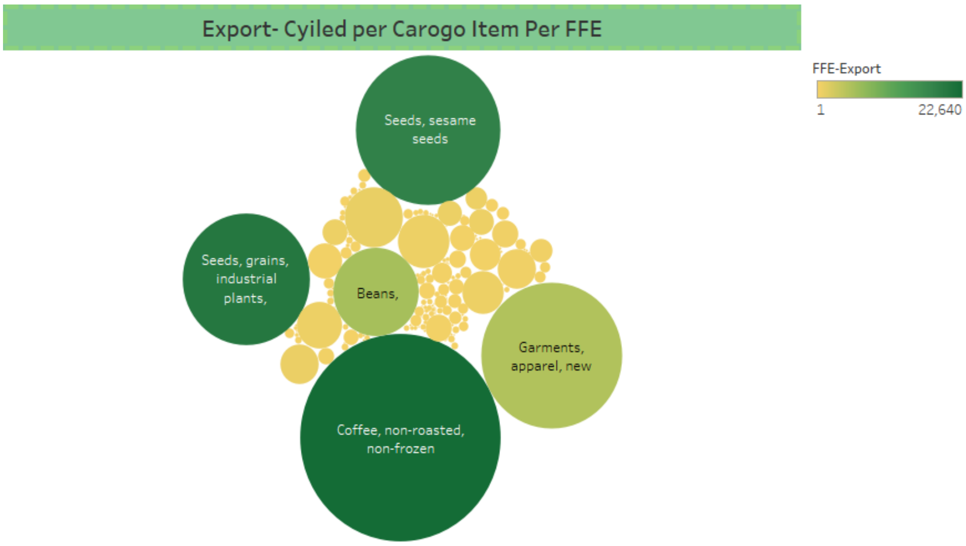
Export- Commodities-Export commodity items with higher CYiled per number of FFE loaded over the years were " Coffee-, Seeds & Sesame Seeds, Garment and Beans. As illustrated in the "Bubble Chart," Fig 4.7, these items appeared bigger in size from the rest of the items groups. In the chart, the colors show the Sum of FFE(Volume) while the Size shows the sum of CYiled. The higher the laod the higher the CYield for the times over the years. However, it worrth nothing that the type of cargo i.e Dry and Refeer had impact on the contribution Yield. Perishable cargos are loaded in a Reefer container, with a certain degree temperature set and adjusted depending on the weather conditions, tends to have a higher rate for similar commodities in DRY cargo, hence with a higher contribution. The 'text table' chart in Figure 4.9 shows the item details and accossiacted CY.Other special type cargos, also had in significant Cyield.

Figure 4-7 Z8 and Z3 Trade per Volume



Source: Circle lines chart extracted from Tableau (Own Elaboration)

Figure 4-8 Top 10 export commodities per CY – Bubble Chart- filtered per FFE and CY



Note: Color shows sum of FFE, Size shows sum of Contribution Yield-Estimate. The marks are labeled by Item Name. Minimum load was 1 and maximum load was 22,640 (Source: Extract from Tableau -Own elaboration)

Figure 4-9 Details of Top 10 Export commodities per cargo Type and CY

CY/FFE- Export

Item Name	Cargo Type	CY/FFE
Diplomatic Cargo	DRY	10,689
Railway equipment	DRY	8,937
Footwear, used, apparel	DRY	8,616
Chemicals	DRY	7,957
Tungsten wire, metal	DRY	7,838
US Government Household Goods and P..	DRY	7,553
Essential oils	DRY	7,435
Peppers capsicum, non-frozen, vegetabl..	DRY	6,887
Books, newspapers, pictures, printed m..	DRY	6,811
Ceramics, stoneware	DRY	6,460

CY/FFE- Export

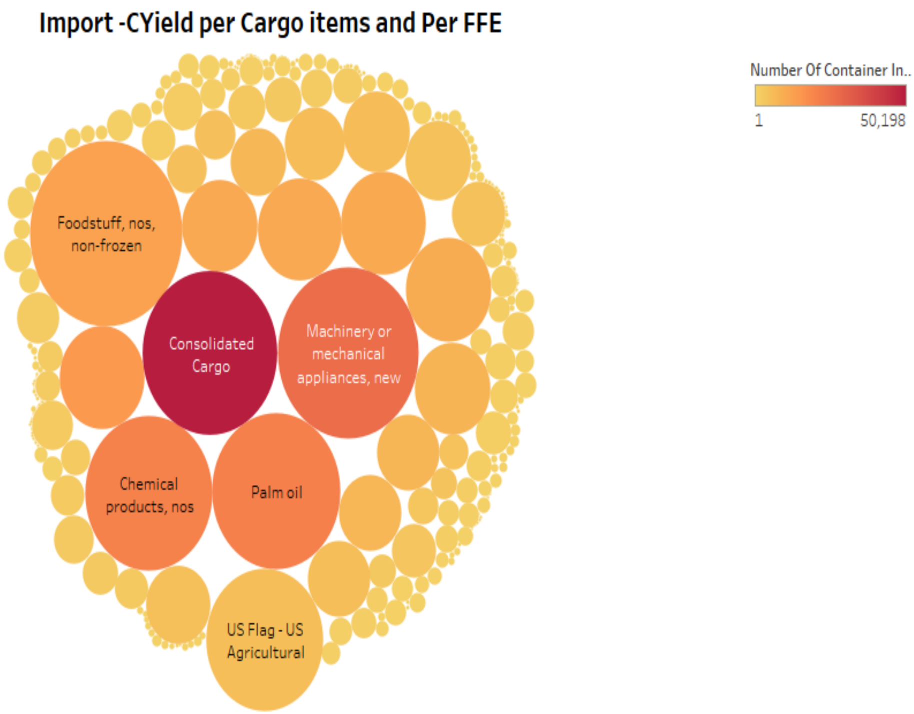
Item Name	Cargo Type	CY/FFE
Sauce, non-frozen, foodstuff	REEF	7,454
Chocolate, non-frozen, foodstuff	REEF	6,989
Coffee, non-roasted, frozen	REEF	5,854
Consolidated Cargo	REEF	5,531
Juice, concentrate, nos, non-frozen, foo..	REEF	5,499
Wine, beverages bottled	REEF	4,802
Coffee, roasted, frozen	REEF	4,370
Tanning extracts, dyeing extracts, pain..	REEF	3,822
Avocado, non-frozen, fruit	REEF	3,436
Raw hides, skins, dry	REEF	3,334

Note: The Data is filtered on TOP Ten Export and Container Size. The Container Size filter keeps 20, 40 and 45. The view is filtered on sum of FFE-Export and Cargo Type (Source: Extract from Tableau -Own elaboration)

Import- Commodities- Import commodity items with higher CYiled per number of FFE loaded over the years were " Foodstuff non-Frozen, Machinery and mechianical appliances,Consolidated Cargo, Palm Oil, checmical products and US agricultural products . As illustrated in the "Bubble Chart," Figure 4.10, these items appeared larger in size from the rest of the items groups. In the chart, the colors show the Sum of

FFE(Volume) while the Size shows the sum of CYiled.The higher the laod the higher the contribution Yield for the times.

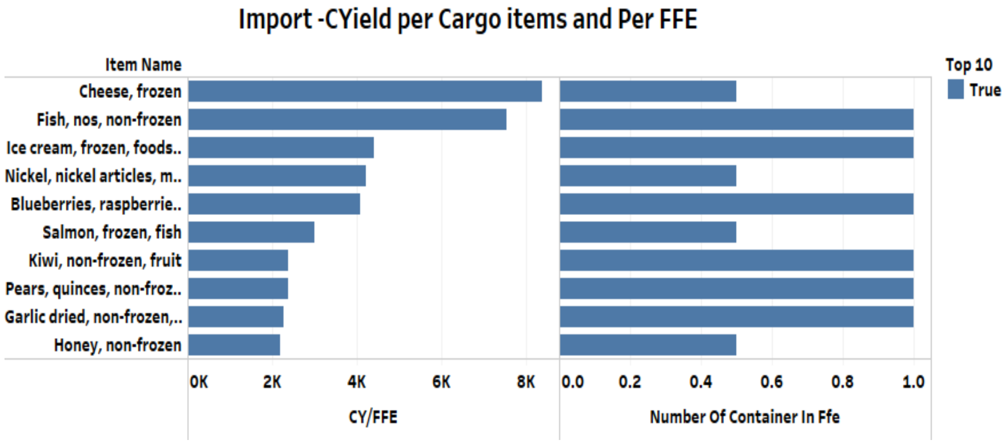
Figure 4-10 Import CYield per Cargo Items and Per FFE



Note: Item Name-Color shows sum of Number of Container in FFE, Size shows sum of Contribution Yield-Estimate. Minimum load was 1 and maximum load was 50,198. The marks are labeled by Item Name. (Source: Extract from Tableau -Own elaboration)

Looking at the same data from CY/FFE (load per one container) perspective, we find that Food items such as Cheese-Frozen, Fish- Frozen, and ice Cream-Frozen had the highest contribution per FFE. It can also be concluded from the nature of the food items that, for imports as in the exports, Reefer container has a higher contribution Yield per FFE than Dry, despite the low volume moved. See Figure 4.11

Figure 4-11 CY/FFE Imports per Cargo Items



Note: Sum of CY/FFE and sum of number of containers in FFE for each Item Name. Color shows details about Top 10 commodities- The view is filtered on sum of Number of Container in FFE and Top 10. The

4.4.3 RQ 3 - What's the Top 10 customers' performance for Import and Export in FFE for the year 2010-2020?

Export Customers

The Exporter Code contained 1440 unique customer codes over the 11 years. Considering the top Ten customers, only Six of them shipped with Maersk since 2010 and one customer since 2011. Taking 2015 as a base year, all ten customers except one have been continually shipping with Maersk. At the end of 2017, one customer with the most minimal load stopped shipping with the company in the same year. Figure 4-12 shows Top 10 customers per volume loaded.

Import Customers

The Importer Code contained 2988 unique customer codes over 11 years. Considering the top Ten customers, only Four of them had shipped with Maersk since 2010 and one customer since 2011. Taking 2014 as a base year, all ten customers except one have been continually shipping with Maersk. One customer started shipping with Maersk in 2014 with three FFE and over 1100 FFE the following year discounted with Maersk from 2016- 2019. In 2020 same customer started shipping with the company with a minimal volume of three FFEs. See Figure 4-13 for the 'highlighted tables' chart extracted from Tableau.

Figure 4-12 Top 10 customers- Export per Volume(FFE)

Export - Top Ten customers by Volume(FFE)

Exporter Code	Year of Year 2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
212001059	110	134	719	999	1,195	654	1,587	2,337	2,909	1,829	983
21200006278	12	25	52	36	53	343	638	306	421	703	518
21200011255				93	222	239	485	502	527	345	194
21200003222	55	29	213	135	160	202	219	167	317	439	248
21200005087	84	29	148	154	168	138	133	178	185	171	70
21200016451						34	106	294	324	376	269
21200002983	79	87	220	240	109	204	89	94	59	58	1
21200005379	266	87	263	122	139	73	250	3			
21200009779		3	11	38	26	23	125	314	251	186	202
21200005873	142	104	124	98	99	41	197	73	79	188	31

FFE-Export: 1 – 2,909

Note: Sum of FFE-Export broken down by Year vs. Exporter Code. Color shows sum of FFE-Export. The marks are labeled by sum of FFE-Export. The view is filtered on Exporter Code, which keeps 10 of 1,440 members. Source: Extract from Tableau- Own Elaboration

Figure 4-13 Import Top Ten Customers Per volume (FFE)

Import - Top Ten customers by Volume(FFE)

Importer Code	Year 2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
212002379	10,415	11,373	17,124	24,924	23,670	28,989	44,741	46,315	20,483	31,599	21,869
21200000598	830	527	285	360	246	437	1,649	762	798	454	732
212001117	759	944	498	649	406	257	122	91	47	28	40
21200015068					167	793	219	482	318	459	717
21200010873			10	200	716	401	114	9	49	1	5
21200014482					3	1,298					20
21200013350				57	399	207	120	12	50	407	36
21200015588					20	550	418	159	49	24	25
21200009805		199	1	43	87	215	3	246	135	53	263
21200008058	100	40	138	127	153	276	59	119	77	67	5

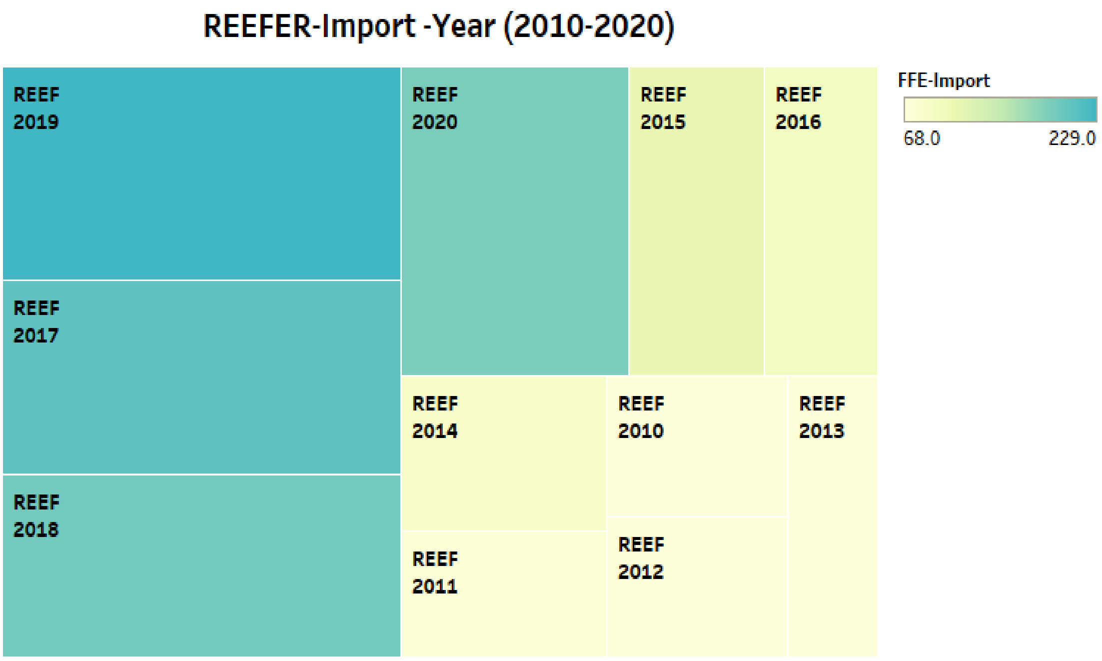
FFE-Import: 1 – 46,315

Note: Sum of FFE-Import broken down by Year vs. Importer Code. Color shows sum of FFE-Import. The marks are labeled by sum of FFE-Import. Details are shown for Importer Code. The view is filtered on Importer Code, which keeps 10 of 2,988 members. Source- Extracted from Tableau- Own Elaboration.

4.4.4 RQ-4 What month, or week has the highest demand for Import Reefer (Refrigerated) containers for the year 2010-2020?

The demand for Reefer container was on an increasing trend since 2016 with variation in the volume of load. In 2019, Reefer container demand was the highest over the years. Figure 4-14 shows the demand for each year.

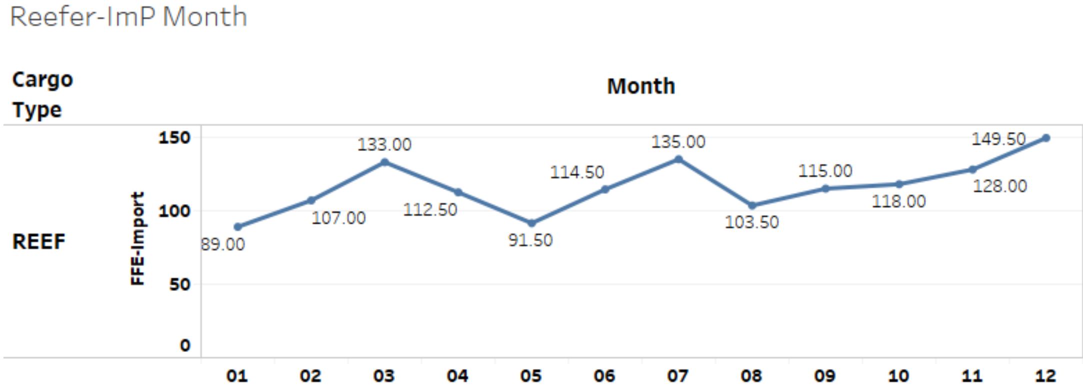
Figure 4-14 Reefer- Import Trend



Note: Cargo Type and Year: Color shows sum of FFE-Import. Size shows sum of FFE-Import. The marks are labeled by Cargo Type and Year. The view is filtered on Cargo Type, which excludes DRY.

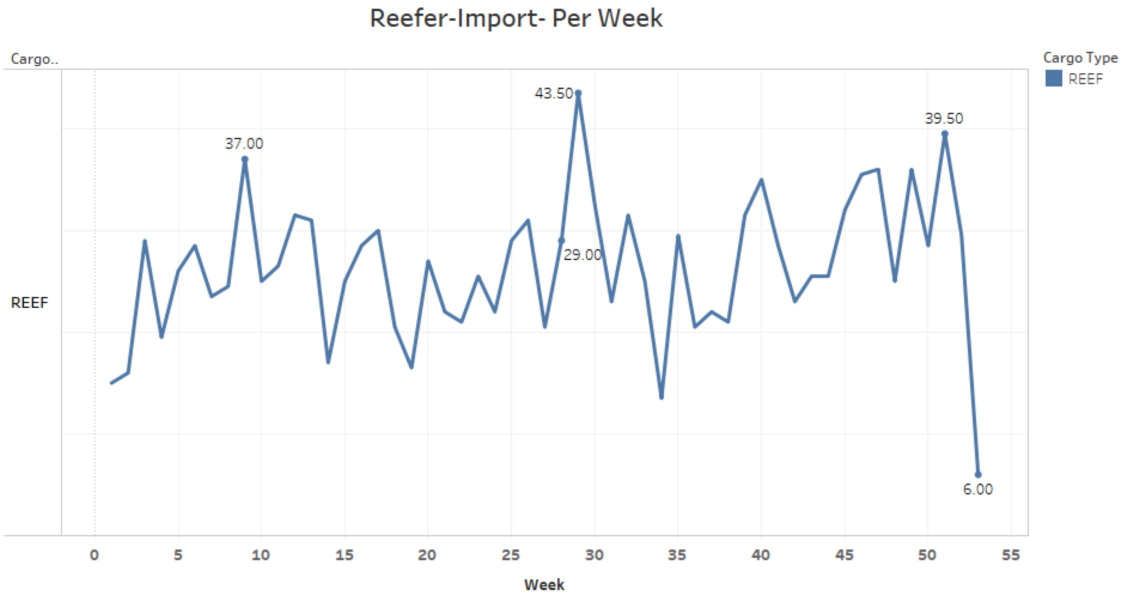
Demand for Reefer containers showed an increasing trend from the month of August to December. March, June, and July registered over a hundred demand for Reefer container. The highest load being month December, Jan recognized the lowest load of 89 FFEs. See figure 4.15.

Figure 4-15 Reefer Monthly Import Volume



Week 29 registered the highest demand, while Week 9 and 51 had a relatively higher demand for refrigerated containers. However, demand in week 34 was the lowest. See Figure-4-16

Figure 4-16 Reefer Weekly Import Volume

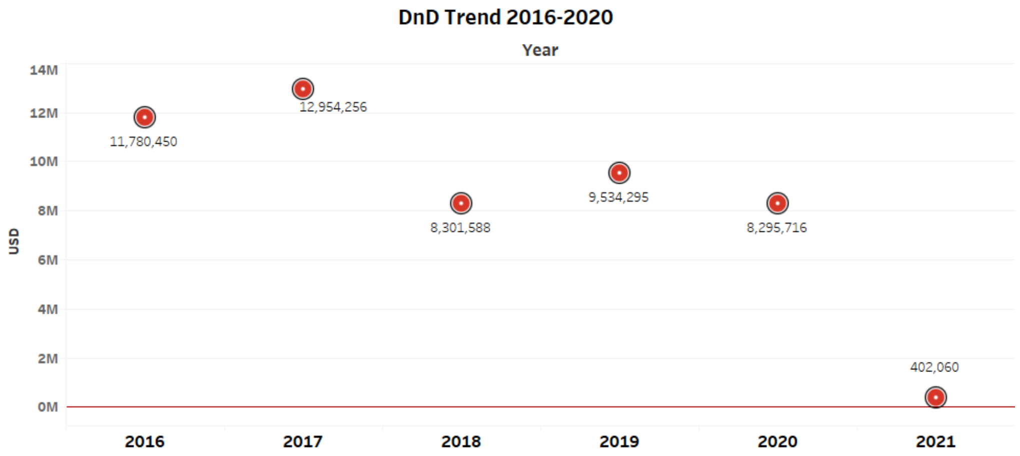


Note: The trend of sum of FFE-Import for Week broken down by Cargo Type. Color shows details about Cargo Type. The view is filtered on Cargo Type, which excludes DRY.

4.4.5 What is the DnD revenue trend per Container Size for the year 2016-2020?

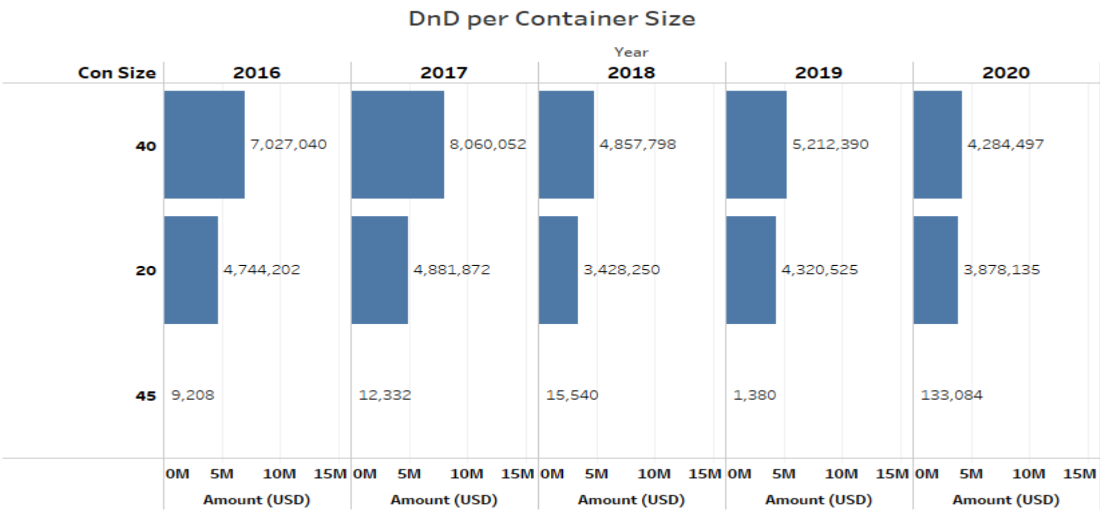
DnD performance compared to 2016 and 2017 showed a reduction. The total import volume reduction in 2018 may have contributed for lower DnD on the year. Overall DnD performance is lower but in steady state since 2018.Year 2021 shows DnD revenue for containers discharged in 2020 and doesn't cover the full year performance. Figure 4-16 shows the trend in Year and amount USD.

Figure 4-17 DnD Revenue Trend 2016-2020



From container's Size point of view 40 Feet containers had higher revenue than the 20 Feet in the last five years under consideration.

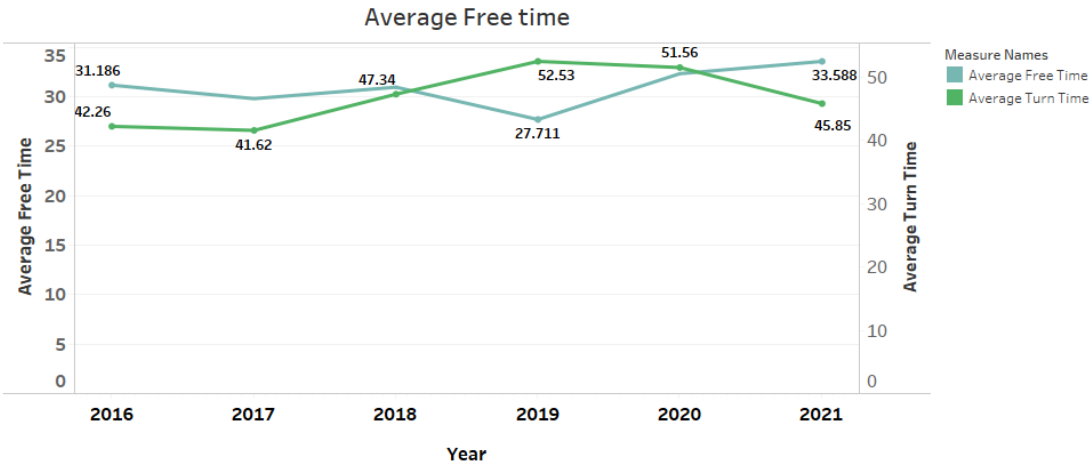
Figure 4-18 DnD Revenue per Container Size



4.4.6 What is the Turn Time and Free Time trend and the 'detention bucket' for the returned containers for the year 2016-2020?

The gap between average Free time and Turn time remained almost steady. The minim average free time was 30.4 days while the max Turn time was 45.7 days. Fig 4-19 shows the trends of Average Free Time and Average Turn Time with the max and min average days for the years 2016 to 2021. Color shows details about Average Free Time and Average Turn Time.

Figure 4-19 Average Free time -DnD



Source: Tableau extract- Own Elaboration

Detention Buckets

The detention buckets show how often the containers get returned as result where most of the revenue comes from based on the number of days. As can be seen from Figure 4-20, DnD revenue is higher for "More than 30 days" bucket. In 2017 a relatively higher DnD revenue was recognized in the "11-30 days" detention bucket. Figure 4-21 shows the number days with each DnD buckets that resulted in revenue gain or loss. Since DnD is calculated based on the number of days over the free time days multiplied by applicable rates, one can notice the lost revenue from "with in free time" buckets.

Figure 4-20 Detention Bucket- DnD in Number of days

Detention Bucket -DnD

Detention Bucket	2016	2017	2018	2019	2020	2021
1-10 Days	349,820	615,643	203,672	245,700	237,666	20,586
11-30 Days	2,298,840	3,920,985	1,392,479	1,763,809	1,870,719	127,110
More than 30 days	9,131,790	8,417,628	6,705,437	7,524,787	6,187,331	254,364
Within Free Time	0	0	0	0	0	0

Year; Amount (USD): 0 – 9,131,790

Note: Sum of Amount (USD) broken down by Year vs. Detention Bucket. Color shows sum of Amount (USD). The marks are labeled by sum of Amount (USD). Source: Tableau extract- Own Elaboration

Figure 4-21 DnD Total number of Days

Detention Bucket -DnD- in number of days

Detention Bucket	2016	2017	2018	2019	2020	2021	Grand To..
1-10 Days	187,758	191,706	81,554	112,956	92,225	9,707	675,906
11-30 Days	240,940	267,774	116,093	192,476	176,458	8,640	1,002,381
More than 30 days	207,368	203,580	128,130	192,928	150,038	6,429	888,473
Within Free Time	465,623	467,201	189,065	155,754	155,152	13,355	1,446,150

Year; Amount (USD): 0 – 9,131,790

Note: Sum of Day broken down by Year vs. Detention Bucket. Color shows sum of Amount (USD). The marks are labeled by Sum of Day. Source: Tableau extract- Own Elaboration

4.5 Dashboard and Stories

The last step in Tableau is preparing dashboard and stories. The different visuals in different worksheet are summarized in this step. This allows to gather all the visual analysis conducted and providing a presentation in a chronological order, like telling stories in an interactive manner. Figure 4-22 illustrates sample Dashboard for the research project.

Figure 4-22 Dashboard and Stories

(Source: Own Elaboration)

By examining the 11 years of datasets from different sources, i.e., Import, Export, and DnD datasets, it was possible to visualize and analyze the data in rows and columns with primarily no meaning. Tableau makes it possible to integrates different data sources and makes the analysis interesting due to its interactive platform and easy-to-use access.

With business knowledge, the right or critical questions asked, and quality data, Tableau presents a simple way to interact with the data to perceive meanings and insights. With the data visualization tool, it was easy to mark peculiar patterns, and it was also possible to analyze the datasets from diverse perspectives.

Overall, the attempt to discover meanings and insights by responding to the research questions was a tangible outcome of this research.

Chapter 5 SUMMARY CONCLUSION AND RECOMMENDATION

5.1 Introduction

This chapter discusses the learning and the researcher's reflection during the full course of the project. Discussion on the insights obtained, conclusion and recommendations are also presented in the chapter.

5.2 Summary of the data visualization and Analytics process of the study.

As indicated in the literature, Analysis of a larger datasets, using Big Data analytics techniques such as Data visualization, helps reveal insights that might have remained hidden. The outcome of the analysis, the insights can help organizations make better decisions regarding their operations. The examination of the datasets to discover insights was a bold but brave move by the researcher as Data quality was not fully known in advance, and there was no guarantee that a hidden insight would be uncovered. In the following section, the researchers Key take ways, and learnings are reflected. The theme of the reflection will be tuned in line with the scope of the project.

Size of the Datasets-The analysis of larger data sets, as reflected in the literature, provided the opportunity to see the movements of the Import and export trends and the DnD revenue performance over the period under examination. The combinations of different data from different sources assisted in visualizing some of the gaps that existed in the import and export shipments. The comparison of Import volume against the DnD revenue performance over the years could be related to understanding the business performance.

The *Tool* applied for the analytics was easy to use, with lots of free training available, user-friendliness, and highly interactive features. Tableau can connect to various data sources and load for analysis and visualization in seconds. Its available charts provide the visuals importantly enough to discover out of the ordinary or events that are behaving differently from the "crowd."

5.3 Conclusion of the Study

The purpose of the Study was to examine Export, Import and DnD Datasets using an advanced Data visualization technique and tool to extract meaning and insights and to describe the results. The study intended to achieve six specific objectives using Tableau desktop, an advanced data analytics and visualization tool and the following results were obtained.

1. To examine and describe the volume (FFE) trend for Import and Export shipments per Trade for the year 2010- 2020.

Both the import and Export shipmen trend showed reduction toward the end of 2020. Import shipments had a higher volume of load than the export. Regarding trades, Z3 trade (Middle East- East Africa) had a strange movement over the years. With repeating and predictable high and low load every other year. Despite the low Export trend, the Import performance, in contrast, remained firm. Z1 and Z8 export performance, despite the low volume movement, stood strong. Intra Africa trade had a steady and minimal load over the 11 years under examination. Z4 or Europe –East Africa trade is the most stable trade of the company, with major highest and lows in terms of FFE moved.

2. To examine and describe what commodities have a higher contribution yield for Import and Export per Trade for the year 2010- 20202

The export activity is dominated by commodities that the country produces, majorly involving Coffee beans and seed and Sesame. However, Garment and apparel were the "new thing," especially for exports in Trade Z1(Americas – east Arica). CY contribution per FFE load was higher for reefer cargo types. Even with the minimal demand movement of the Reefer containers to the area, the contribution per load was significantly higher than the dry cargo types. The Import business is mostly loaded with food items, types of machinery, and edible oil. Z8 (far east Africa) remained the preferred POR for the items imported and POD for export that came out from the country. CYield for the imports came from perishable goods that were loaded with refrigerated (Reefer) containers. Items such as Cheese-Frozen, Fish- Frozen, and ice Cream-Frozen had the highest contribution per FFE.

3. To examine and describe top 10 customers' performance for Import and Export in FFE for the year 2010-2020.

Maersk had a total of 1440 and 2988 Unique customer codes for Export and Import respectively. The Top 10 customers per volume moved for export customers showed reductions for all customers except one. Customer 21200009779 started shipping with Maersk in 2011 and had an increased volume shipped in 2020. Customer 212001059 took the lion share of the export business. A total of Six customers had been shipping with Maersk since 2010 while 3 started shipping in, 2011,2013 and 2015. Customer 21200005369 discontinued shipping with Maersk in 2018 after eight years of business with Maersk.

The Import shipment however was dominated by customer 212002379 loading on average 25K FFE per year from 2010-2020. Despite the decrease in volume for overall import shipments to Ethiopia, customers 21200000598, 21200005068, 21200015588 and 21200000805 had a higher load in 2020 than 2019. Customer 21200015588 loaded with Maersk in 2014 and 2015 but discounted business with the company up the end of 2019. In 2020, same customer started loading with Maersk with 20 FFE

4. To examine and describe the month, or week that has the highest demand for Import Reefer (Refrigerated) containers for the year 2010-2020.

While the demand for reefer containers compared to other containers types remained low, the demand for Reefer container was on an increasing trend since 2016. Year 2019 registered the highest load of Reefer containers. The demand for such type of containers was over 100 FFE in the month of March, June, and July. But overall demand for reefer containers showed an increasing trend from August to December. December registered the highest load while the demand was low for the month of Jan over the years under investigation.

The weekly demand for the Reefer container was strong in Week 29, while weakest demand was registered in Week 34. Despite the highest demand in the month of December, the week wise analysis of the demand for reefer container indicated a week damned at week 52 which is towards the end of December.

5. To examine and describe the DnD revenue trend per Container Size for the year 2016- 2020

The DnD revenue over the yeas showed a decreasing trend. 2018 showed a significant drop of revenue from 2017 which was the highest DnD revenue with close to 13 million. Looking at the DnD revenue from container size perspective, it was found out that 40 Feet container contributed more revenue than 20 Feet.

DnD revenue reduced in relation to the volume of load for import shipments in 2018. 2017 registered a total volume of 52.5K. At this same year, DnD revenue was 12.9 million. As the volume reduced the DnD revenue was negatively impacted.

6. To examine and describe the Turn Time and Free Time trend and the ‘detention bucket’ for the returned containers for the year 2016-2020.

The Free time and Turn time significantly affect the DnD revenue. Free time given by Maersk between 2016 and 2020 was on overage 30 days. whereas, turn time was on average 46 days. Based on the detention bucket analysis, the DnD revenue was the highest for containers that have lasted more than 30 days before return. The number of Free times based on the detention bucket analysis revealed reduction from 465K days to 155k Days in 2020. This could be because of timely return of the containers or a reduction in the number of free days given by Maersk**.**

5.4 Recommendations

Basis the study's specific objectives and examination of the Export, Import and DnD datasets, the following recommendations are forwarded:

1- The route cause why the volume reduced for both Export and Import shipments must be further analyzed to identify factors affecting the volume movement.

The volume performance should be compared against other shipping lines and the total market to identify any gaps.

The peculiar export shipment in Z3 trade should be further analyzed to understand the real cause for the volume movement. The reduction in Import volume in Z8 signals the minimum number of available containers(load) in the trade. Since the reduction in Import directly affects the availability of containers for export, focus should be given to trades with significant volume reduction.

2- In addition to the cargo loaded with Reefer containers that have a higher contribution per FFE, Garment and Apparel showed a strong move to Z1 trades. Making sure available containers and shipment schedule to support this trade will result in higher contribution Yield per FFE
3- Due attention must be given to Customer 212001059 and 212002379 that dominated the Export and Import Business, respectively. Customer 21200005369 should be contacted to find out why they are not using the Maersk service anymore after 8 years' business relationship to address any challenge that can be resolved.
4- In order to make sure of Reefer containers availability, understanding why the strong demand existed in the month of August to December and in week 9, 29 and 51 should be addressed to proactively resolve any shortage for such container types that may arise.
5- DnD revenue performance went hand in hand with the total import shipment over the years. Due attention must be given when setting volume target for future years as it impacts DnD revenue. Availability of 40 Feet containers insures steady revenue performance.
6- The gap Between the free time and Turn Time over the years indicates that containers are not returned with in the agreed time and hence resulting in DnD charges. If the DnD revenue to show stable performance, the total number days must be above 203k days without any rate increase. A rate increase or a reduction in the number Free Time can help convert some of the "within free time" days to revenue.

5.5 Recommendation for Future Study

This research Project Examined the Export, Import, and DnD datasets using the Data visualization technique. The examination only considered internal and structured data for the analysis. The analytics technique applied was descriptive using the data visualization technique and tool. As indicated in the literature, understanding what is going on based on historical data is the first step of analytics. However, understanding why things are the way they are is of great importance to predicting future outcomes. Hence recommend incorporating Predictive Analytics to understand the research's findings to obtain additional actionable insights for future studies.

References

Borgi, T., Zoghlami, N., Abed, M., Saber, N. M., & Naceur, M. S. (2017). Big data for operational efficiency of transport and logistics: a review. *IEEE International Conference on Advanced Logistics and Transport (ICALT)*, 113–120. https://doi.org/10.1109/ICAdLT.2017.8547029

Cartledge, C. (2016). *How Many Vs are there in Big Data?*

CGMA. (2016). Business Analytics And Decision Making. *Baseline*, 24.

Creswell, J. W. (2009). Research Design (Qualitative, Quantitative and Mixed Methods Approaches). In *Sage* (Vol. 8). https://doi.org/10.2307/1523157

Davenport, T. H. (2013). Analytics 3.0. *Harvard Business Review*, *5*, 64–72.

Davenport, T. H., & DalleMule, L. (2017). What's Your Data Strategy ? *Harvard Business Review*, *59*(4), 112–121.

Davenport, T. H., & Prusak, L. (1998). Working knowledge: How organizations manage what they know. *Harvard Business Press.*

Elgendy, N., & Elragal, A. (2016). Big Data Analytics in Support of the Decision Making Process. *Procedia Computer Science*, *100*, 1071–1084. https://doi.org/10.1016/j.procs.2016.09.251

Heang, R., & Mohan, R. (2017). Literature review of business intelligence. *Journal of Business, Engineering, and Science*, *10*(2), 1–10.

Jagadish, H. (2015). Big Data and Science: Myths and Reality. *Big Data Research*. https://doi.org/10.1016/j.bdr.2015.01.005

KMAKI, J. (2016). *DATA DRIVEN DECISION MAKING IN DIGITAL WORLD*.

Kothari, C. . (2004). Research Methodology Methods and Techniques. In *New Age International*.

Kubick, W. R. (2012). Big Data , Information. *Clinical Trial Insights*, *21*(2), 26.

Kumar, U. D. (2017). *Business Analytics Business: The Science of Data-Driven Decision Making*.

Maersk. (2021). Teamsite. https://teamsite.maerskgroup.com/sites/bu-sma/countries/africa_region/horn-of-africa/Pages/Ethiopia.aspx

Maersk. (2021). *Biplastforms*. https://teamsite.maerskgroup.com/teams/MLI-NewBiPortal/SitePages/BiPlatforms.aspx

Negash, S. (2004). Business Intelligence. *Communications of the Association for Information Systems*, *13,Article*(February). https://doi.org/10.17705/1CAIS.01315

Nykänen, E., Järvenpää, M., & Teittinen, H. (2016). Business intelligence in decision making in Finnish enterprises. *Nordic Journal of Business*, *65*(2), 24–44.

Olszak, C. M., & Ziemba, E. (2007). Approach to Building and Implementing Business Intelligence Systems. *Interdisciplinary Journal of Information, Knowledge, and Management*, *2*, 135–148.

Power, D. J. (2008). Understanding data-driven decision support systems. *Information Systems Management*, *25*(2), 149–154. https://doi.org/10.1080/10580530801941124

Pwc. (2019). *CEOs' curbed confidence spells caution 22nd Annual Global CEO Survey*.

Russom, P. (2011). Big data analytics. *TDWI Best Practices Report Fourth Quarter*, *19*(4), 1–34.

Sadiku, M. N. O., Shadare, A. E., Musa, S. M., & Akujuobi, C. M. (2016). Data visualization. *International Journal of Engineering Research And Advanced Technology*, *12*, 11–16.

Sanders, N. (2014). *Big Data Driven Supply Chain Management: A Framework for Implementing Analytics and Turning Information Into Intelligence*.

Schrack, A., & Warner, T. (2020, April 16). *How to Begin Making "Data-Driven Decisions" Using Data Integration*. Safe Software. https://www.investopedia.com/terms/d/data-analytics.asp

Sharda, R., Delen, D., & Turban, E. (2014). *BUSINESS INTELLIGENCE AND ANALYTICS: Sytesms for Decision Support*. PEARSON.

Storey, V. C., & Song, I.-Y. (2017). *Big data technologies and Management: What conceptual modeling can do*. *108*, 50–67. https://doi.org/10.1016/j.datak.2017.01.001

Tableau. (2021). *What is business intelligence? Your guide to BI and why it matters*. https://www.tableau.com/learn/articles/business-intelligence

Watson, H. J. (2016). Creating a Fact-Based Decision-Making Culture. *BUSINESS INTELLIGENCE JOURNAL*, *21*(2), 5–9.

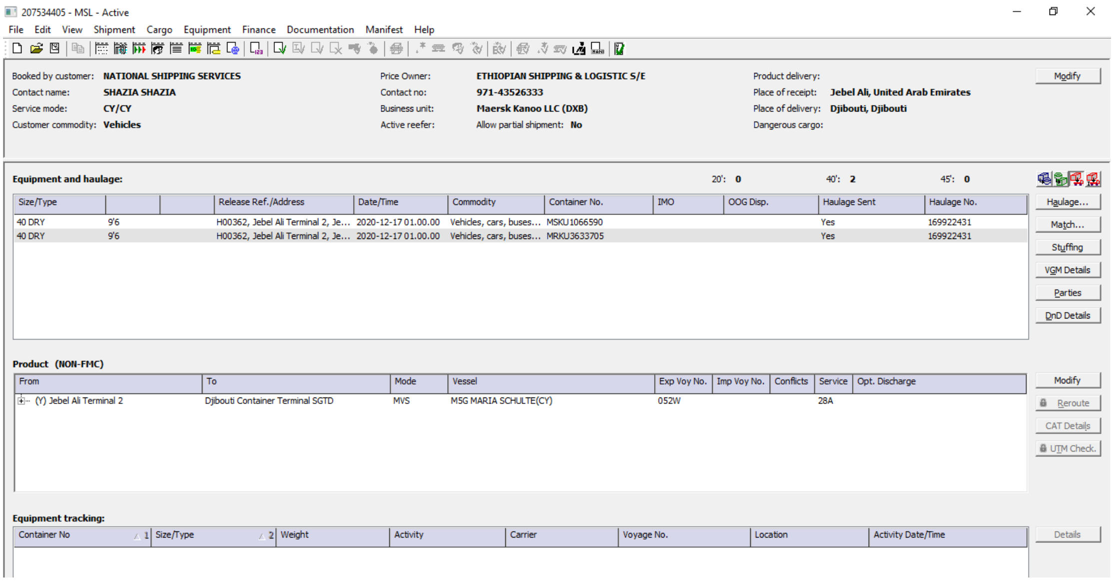
Watson, H. J., & Wixom, B. H. (2007). The Current State of Business Intelligence.

Computer, *40(9)*, 96–99.

Yin, R. K. (2003). Study research design. *Applied Social Research Methods Series*, *5,* 1–53. https://doi.org/10.1016/0002-9149(74)90005-8

APPENDICES

Appendices 1 Shipment Summary- GCSS Extract



Appendices 2 Import and Export Initial Columns

Columns	Description
ATF Port Dep 1 Year	year
ATF Port Dep 1 Yr/Month	month
ATF Port Dep 1 Yr/Week	week
BkdBy Cust Name	name of the agent or customer that made the booking
BkdBy Cust Country Name	country of the agent or customer that made the booking
Shipper Cust Name	the party that ships (hands the shipment) the cargo- agent of the consignee
Shipper Cust Country Name	country of the shipper
BkdBy Cust Code	Code- identifier the customer or the agent that placed the booking
BTN Name	commodity group name- e.g. Textile and Apparel (Export), Beverages (for Import)
Commodity Name	name of the commodity-footwear (Export), Red Bull (Import)
Cargo Classification Description	cargo grouping name (Commercial cargo, Aid cargo,)
Cargo Type	Dry or Reefer (A refrigerated Container-cargo)
Consignee Cust City Name	city of the consignee-CONSIGNEE Refers to the individual or firm specified on the Bill of Lading and legally authorized to receive the shipped goods

Consignee Cust Cluster Name	branch/cluster offices of Maersk (the consignee is located)
Consignee Cust Code	the code that identifies the consignee customer
Consignee Cust Country Name	country of the consignee2
Consignee Cust Name	consignee customer name
Shipper Cust Code	The code that identifies the shipper
Consignee Cust Segment 1st	Additional description of the consignee- If Key client or not
Consignee Sales Control	consignee sales control
Container Size	container size
Contractual Consolidated Cust Code	Code/Identification number special contract
Contractual Consolidated Cust Name	Name of Customer that has a special contract
Contractual Cust Cluster Name	branch/cluster offices of Maersk (the contractual customer is located)
Contractual Cust Code	Identification number of the contractual customer
Contractual Cust Country Name	Country of the contractual customer
Contractual Cust Name	contractual customer name- name of the person/company with special contract
Delivery Service Mode	delivery service mode- Deliver at the port or at consignees' yard
DIPLA City Name	First discharge place of the cargo
Head Haul/Back Haul	Direction of the cargo move import/export respectively
Item Name	Specific item of the commodity- spare parts for Vehicle (Commodity group)
LOPFI City Name	First load port-place other than final port of loading
POR City Name	Port shipment was received (Load port)
POR Cluster Name	branch/cluster offices of Maersk-Cargo were received
POR Country Name	Place of Receipt Country Name
POD City Name	Place of Delivery City Name -Port where cargo is unloaded from the vessel
POD Country Name	Place of Delivery Country Name -Port where cargo is unloaded from the vessel
Price Owner Cust Country Name	price owner customer country name- Person/agent negotiating the price
Price Owner Cust Name	price owner customer name
Receipt Service Mode	Place of shipment received CY-Container Yard, SD Store door
Route	The course or direction that a shipment moves - e.g. From East Africa to Asia
Shipment Number	A number identifying the cargo shipped
Shipment Operator	Company/Brands MLL (Maersk Line Limited), MSL (Maersk Line), SCL (Safmarine Line)-

Est Basic Freight	Estimated Basic Freight- Freight- The price paid to the carrier for the transportation of goods or merchandise by sea from one place to another
Est CYIELD	Estimated Container Yield- The Contribution Margin of a shipment plus/minus Flow Adjustment (to account for container positioning costs). Abbreviated CYield or CY.
Est Net Frt	Estimated Net Freight - cf Basic freight
FFE	Forty Feet Equivalent- the size of a container- total number
TON	Tonnage- Weight of the cargo measured in ton

Appendices 3 DnD Initial Columns

Initial Column Names	Description
Vsl/Voy	Vessel name and voyage number
T/P No	Transport Document/ a unique number identifying the cargo shipped
Line	The course or direction that a shipment moves - e.g. Far East - Horn of Africa (Z1)
Consignee	The individual or firm specified on the Bill of Lading and legally authorized to receive the shipped goods
Consignee Name	Name of the consignee
Equip Id.	The number that identifies the container ("Boxes"
Equip. Type	dry or Reefer (A refrigerated Container- cargo)
FT Start Date	Discharge Date- Free time starts to count
FT Start Time	Discharge time- Free time starts to count
Expiry Date	date free time ends
Expiry Time	time free time ends
Ch End Date	calculation date- date DnD was calculated
# of days	number of days from discharge to return date
Amount (USD)	revenue calculated (Rate x number of days)
Rsn RC	Revision and recalculation done
Calculated Date	date calculation done by
Calculated By	CXEDF04- the tool that calculated the DnD