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Decision support system for port terminals: Design and development of a business intelligence tool

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Abstract

The exponential growth in the volume of maritime cargo has presented significant challenges for ports, underscoring the urgent need for digitalized processes and more efficient solutions aligned with the Maritime 4.0 vision. However, there is a gap in research focusing on applying Business Intelligence (BI) tools to optimize port terminal operations. This article addresses this gap by developing a BI tool to characterize the flow of container delivery and pick-up services at a Portuguese port terminal, utilizing the CRISP-DM methodology. The tool, built using Microsoft Power BI, not only eases the extraction and correction of data inconsistencies but also presents key operational indicators through visually appealing dashboards. These dashboards enhance the understanding of both current and future operational states, leading to more informed and agile decision-making. On the terminal under study, the implementation of this BI tool revealed that scheduling is done with an average lead time of just 32 minutes in the current year, with 47% of services being scheduled in advance and only 21% adhering to their designated time slots. These results corroborate the challenges faced and demonstrate the critical role of data in monitoring operational performance. By addressing these challenges, this study not only enhances logistics flow analysis and reduces terminal congestion but also demonstrates the significant impact of BI tools on achieving Maritime 4.0 goals. The findings establish a solid foundation for future BI applications in the maritime sector, highlighting the transformative potential of digital solutions in optimizing seaport operations.

Keywords: Business Intelligence; Data Mining; Performance Indicators; Dashboard; CRISP-DM; Seaports; Maritime 4.0

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1. Introduction

Maritime transport plays a crucial role in global trade, being the main method of moving cargo on a large scale moving 12 billion tons in 2022 [1]. Containers are the main way of storing cargo, as they can be transported and handled by several vehicles, which is why the volume of containers shipped is expected to grow by 3% annually between 2024 and 2028 [2].

The relevance and growth of this method of transport highlights a variety of challenges regarding the efficiency and effectiveness of port logistics operations, especially at container terminals [3]. To ensure the effectiveness of operations involving terminal services, they must ensure that containers enter and leave the terminal quickly, mitigating any problems that may occur at peak times. For this purpose, scheduling systems were implemented for the lorries to speed up entry into the terminals and thereby reduce waiting times and, consequently, negative impacts on emissions. However, these measures have not been enough to solve these problems [4].

These logistical and environmental challenges are fostering a constantly growing need for ports to innovate, giving rise to the concept of the Smart Port, with the aim of overcoming disruptions in the supply chain through technological applications. With these technologies and because of the automation of processes are large amounts of data, collected through different types of mechanisms, requiring correct treatment and processing, to achieve an information value to support the decision-making processes [5].

Nowadays, many ports rely on manual solutions that cause waste [5]. This is why digitalization is essential for the modernization of ports, requiring the integration of systems and collaboration between stakeholders [6]. This involves creating a structure that collects and processes data in real-time, using business intelligence tools to better control port operations [7].

This paper aims to support the process of digital and ecological transition in transport, logistics and port operations through a decision support system developed using Power BI to structure and accelerate the process of analysing data. This study's contribution includes the creation and development of a practical decision support tool based on Business Intelligence to increase the efficiency and resilience of port logistics operations. The paper is structured as follows: Section 2 reviews digital transformation in port logistics. Section 3 describes the problem at the terminal under study, the objectives set, and the methodology implemented. Section 4 presents the main results of the tool built, specifically the indicators and dashboards. Section 5 evaluates the tool with a SWOT analysis. Section 6 summarizes the article's contribution, limitations and future research directions.

2. Theorical Background

2.1. Digital Transformation in Port Logistics

The history of seaports points out five distinct generations, each one marked by advances in the adoption of technologies and the redefinition of operations [1]. The first generation, before 1950, was characterized by manual loading and unloading operations, using paper-based procedures that switched to an electronic format (EDI). In the second generation, before 1980, ports became value-added service centers, reflecting the increase in the movement of raw materials, where the first port communication systems (PCS) appeared. The third generation, from 1980 onwards, saw the emergence of intermodal transport and the adoption of information technologies to improve operational efficiency, with the implementation of terminal operating systems (TOS) integrating data from different technologies and subsystems. The fourth generation, from 1990 onwards, led to the integration of port companies into common administrations and the development of technologies that automated processes. The fifth generation, from 2010, introduced the concepts of "Smart Port", "Industry 4.0", "Digitalization", and "Sustainability", where ports adopted smart devices and mobile applications to optimize traffic and cargo flows, while also integrating various control centers into a central system. Building on these advancements, the concept of "Maritime 4.0" emerged, further extending the integration of advanced digital technologies and data-driven approaches to enhance operational efficiency, decision-making, and sustainability in maritime logistics [8], [9], [10]. The main aspects of each one of the three generations of digitalization in ports are summarized in Table 1.

Table 1. Main aspects of each generation of digitization, adapted from Heilig et al. (2017).

Generation	Technology	Purpose	Contribution	Obstacle
1st (1950 - 1990)	EDI, PCS, TOS	-Transformation of all information exchanges between the various companies using the port from physical to electronic methods	-Better planning of process execution due to the availability of information	-Low adherence of the port community to the systems created, as companies do not abdicate from using physical documents
2nd (1990 - 2010)	RFID, TAS, Laser	-Automation of terminal activities	-Increased efficiency and operational capacity	-Collected information is static -Low adoption of the truck appointment system (TAS)
3rd (since 2010)	Mobile Apps, Cloud, Smart devices	-Creation of intelligent processes that integrate port activity	-Better coordination and monitoring of port activity	-Inefficiencies in information flow -A certain reluctance among stakeholders to use disruptive processes

2.2. Exploration of Data and Business Intelligence

Businesses collect and store countless data inherent to all their activities, and the challenge lies in the ability to select and analyse data efficiently [11], intending to extract added-value information that is effective in supporting decision-making [12].

This situation has triggered the birth of areas such as Data Science to establish methodologies, such as the Cross-Industry Standard Process for Data Mining (CRISP-DM) cycle, and techniques, such as Data Mining, designed to structure and give tools for analysing data [13]. Data mining is an approach to data analysis that has two main objectives: description, which involves discovering patterns, and prediction, which anticipates future behaviour through the present [14]. These concepts are no longer new, although they are more relevant now, given the ease of gathering data and the urgent need to transform it into valuable information.

Data quality is particularly important in this area. To guarantee this quality, according to [15] there are five dimensions of data analysis, giving them a certain level of quality: (a) completeness, regarding the scope of the data; (ii) accuracy, in terms of the correctness of the data; (iii) timeliness, associated with the temporal relevance of the data; (iv) consistency in the way the data is presented; and (v) accessibility, related to how easy it is to obtain the data quickly, ensuring an agile approach to data-based decision-making. Failure in any dimension can result in low data quality and, consequently, erroneous decisions and loss of competitive advantage [16]. Therefore, establishing quality control policies and processes is essential to guarantee data that supports strong decisions [17].

Linked to data processing is the concept of Business Intelligence (BI), described as a discipline that combines the whole infrastructure of data extraction, processing, selection and visualization [18].

The construction of a BI system depends on the specific needs of each company which requires strategic planning to process the information created to ensure that the solutions created are tailored to the company's objectives [19]. Several proposed architectures for this system cover different levels of implementation. The proposal of Chaudhuri described in [20] consists of five: Data Sources; Data Movement (ETL); Data Warehouse Servers and Data Marts; Mid-tier Servers; and Front-End Applications.

3. Motivation, Objectives and Methodology

The increase in the volume of containers in the ports, as is expected in the port where this study is taking place, causes pressure on the terminal's operations, exposing inefficiencies that need to be addressed to meet the demand growth. One major inefficiency is, usually, the lack of organization in logistical services due to demand unawareness, causing operational imbalances.

To address this challenge, many seaports have implemented scheduling systems through dedicated platforms. However, in some ports, when this type of solution is not accompanied by an effective utilization strategy, it may not prove to be sufficient and efficient. Furthermore, technological growth without strategic planning has led to 'data/information islands,' i.e., systems with dispersed data across different applications without integration, resulting in a shortage of agile information flows to organize the port's logistics and dynamics, causing delays and disruptions.

This article proposes the development of a Power BI tool to extract and transform data from logistics operations, providing a quantitative analysis of the current and future situation, which is essential to support decision-making and overcome inefficiencies. To fulfil this purpose, a methodology from Data Science (named CRISP-DM), was adopted. Figure 1 shows the methodology adopted, around its 6 phases, as well as the main inputs and outputs in the context of this practical study.

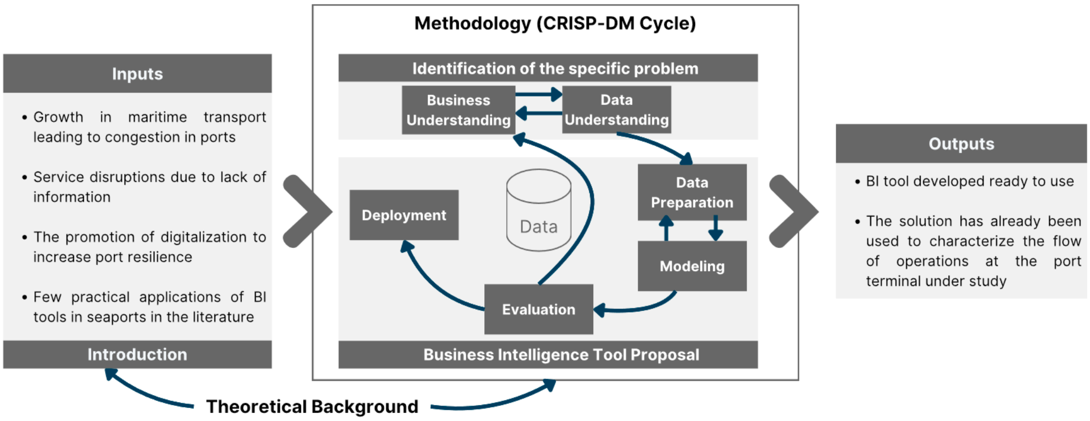

Fig. 1. Methodology adopted based on CRISP-DM Cycle

In the first phase, Business Understanding, several meetings were held to acquire a comprehensive understanding of the business, identifying causes of problems and opportunities for improvement in data analysis and decision-making processes.

In the second phase, Data Understanding, the data sources needed to meet the analysis requirements were identified. Two data sources were identified: (i) the scheduling system (known as JUL), which covers previous schedules made in a dedicated application; and (ii) the operating system (known as GTOS), which supports all the planning, execution and control activities of the terminal's operations. In terms of data quality, a detailed inspection was carried out to check the integrity of the data sources, namely in terms of completeness, accuracy and consistency, i.e. ensuring that they were complete, with uniformly formatted data and free of null or duplicate records. Any unconformities discovered were documented through profiles for further treatment in the BI system and the source system. To exploit the integration of the sources, a common attribute was searched in both datasets, which was not found.

The third phase, Data Preparation, began with the treatment of unconformities found in the previous phase using Power Query, which involved cleaning operations and creating new variables. To diversify the analysis options, a compound key was built to directly cross-reference the data from the initial systems (known as INT). Once this processing was complete, the final attributes and records to be uploaded to the Data Warehouse were selected, excluding those that lost their added value due to their uniqueness or duplication of information. After uploading, the performance indicators considered essential by the stakeholders were defined.

In the fourth phase, Modelling, the Data Warehouse was designed using dimensional modelling to represent the interactions within the data tables, using Snowflake and Constellation Schemas. Dashboards were then developed to display the main performance indicators in an appealing and intuitive interface.

In the fifth phase, Evaluation, the solution was assessed using a SWOT analysis, especially the dashboards, to see if this new BI system can provide a robust analysis of the terminal's systems and support decision-making. In the sixth and final phase, Deployment, the stages of the process were documented, so they could be replicated or adapted to other contexts.

4. Results

This section discusses the results achieved by defining Key performance indicators and incorporating them into the Business Intelligence tool's dashboards. These results have provided a deep understanding of the logistics processes at the terminal under study by providing value-added information.

4.1. Key Performance Indicators Definition

The definition of the Key Performance Indicators (KPI) has considered the scope of the data collected and the requirements raised by the stakeholders, according to the context of the seaport under study.

Three objectives/themes were the basis for defining the KPI and subsequently structuring the information on the dashboards of the BI tool developed, considering the universe of data from the two datasets used. The first concerns the characterisation of appointments using data from JUL (***JUL Analytics***). The second concerns characterizing the services provided at the terminal under study by road, using data from GTOS (***GTOS Analytics***). Finally, a third objective is concerned with characterizing the behaviour of the services performed compared to the appointments made, using the cross-referencing of JUL data with GTOS data (***INT Analytics***).

Based on these three objectives, the main decision support metrics were defined. Thus, from an initial set of 30 attributes, 14 main KPIs were created, as shown in Table 2.

Table 2. Some KPI for decision support on logistics services at a port terminal.

KPI	Description	File / Theme
No. Appointments	Unique appointment count.	***JUL Analytics***
% Cancellation	Percentage of cancelled appointments.	
Average Appointment Advance	Average time in advance (minutes) with which appointments are created about the start of the time window.	
Total Containers per Appointment	Number of containers handled by appointment.	
No. Services	Unique service count.	***GTOS Analytics***
Average Duration of Service	Average time (minutes) taken per service.	
% Entry and Exit Same Time Window	The efficiency with which services are performed on time.	
Availability Time Window	Unused capacity within a time window.	
Containers Delivered and Picked Up	Container handling volume.	
% Scheduled Services	Percentage of services scheduled in advance.	***INT Analytics***
No. Scheduled Services	Total services scheduled in the integrated dataset.	
% Compliance	Percentage of services completed within the scheduled time window.	
Average Entry Delay	Average time (minutes) of delay in truck’s entry.	
Average Exit Delay	Average time (minutes) of delay in truck’s exit.	

This set of indicators is intended to measure and monitor the port's operational performance, particularly about logistics flows at the terminal under study. Some examples of dashboards that are part of the tool developed in the context of this study, will be presented in the next subchapter.

4.2. BI tool for Decision Support in a Port Terminal

In line with the KPI identified and reported in the previous section, three categories of dashboards were built (***JUL Analytics***; ***GTOS Analytics***; ***INT Analytics***), each one with autonomous operation, presenting a set of KPIs in context, with drill-down mechanisms for more detailed analysis of the information. Some of the dashboards in the BI tool will be introduced, where the top left corner of each one identifies the source file and the object of analysis.

The "Categories view" dashboard (Figure 2) displays two main indicators dynamically, depending on the category selected. Once the category has been chosen, the top graph shows the Average Appointment Advance, and the bottom graph shows the No. of Appointments for each value within the category that can be viewed daily, as a total or as a percentage of the total. The analysis can also be expanded by selecting another category to include in the legend.

The importance of this dashboard lies in its ability to analyse appointment data across various categories, enabling users to identify category-specific trends and insights for more targeted decision-making.

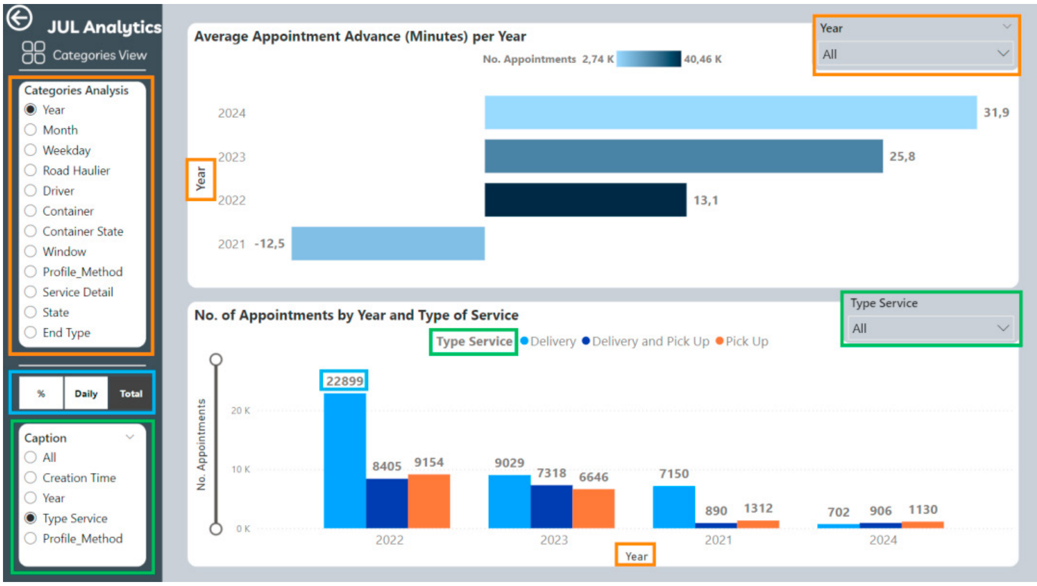

Fig. 2. Categories View Dashboard – JUL Analytics

The "Availability" dashboard (Figure 3) displays the Time Window Availability over the week chosen by the user. The operator's capacity per hour, which affects the calculation of this indicator, can be easily set to follow the supply and demand trends of the port terminal under analysis.

This dashboard uses colours to indicate terminal utilization over time: red show higher utilization, while green indicate lower terminal utilization. Thus, this dashboard presents a simple and useful visual interface design to offer critical information for both terminal operators and transport companies. It facilitates effective resource allocation management for operators and enables transport companies to plan their operations in advance, thereby preventing unnecessary congestion during peak periods at the terminal. Furthermore, the utility of this visual is reinforced by the future strategic goal of ports to universally adopt advanced scheduling across all service operations.

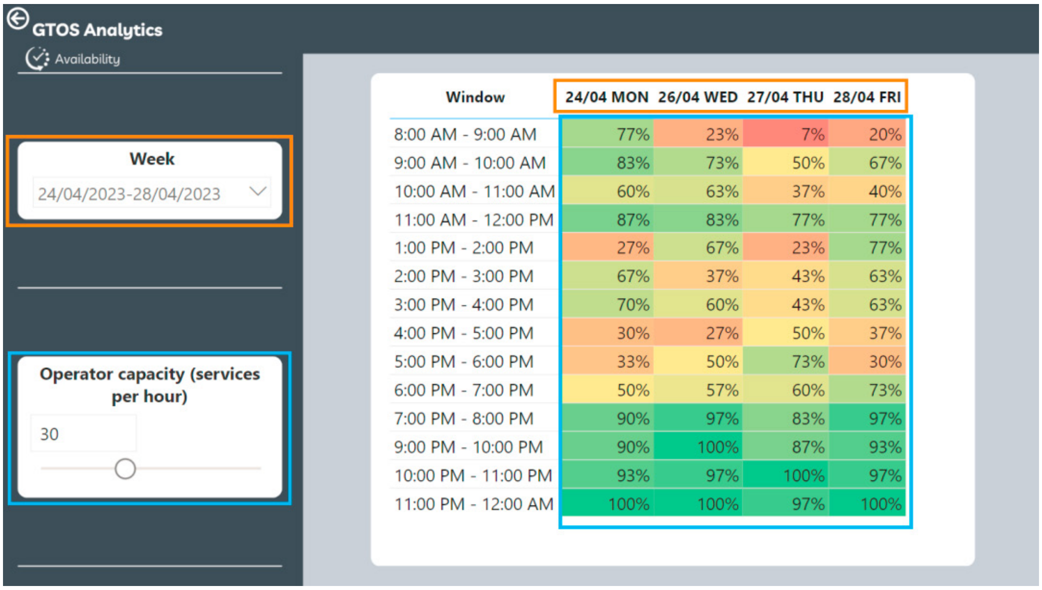

Fig. 3. Availability Dashboard – GTOS Analytics

The “Time View” dashboard (Figure 4) contains the data that has been combined between the two systems. In this dashboard, the user can choose the indicator to analyse in the graphs, where the first comes from JUL (No. of Schedules), the second from GTOS (No. of Services) and the third corresponds to the ratio between the two (%Services Scheduled).

The upper graph of the dashboard shows the absolute values of the chosen indicator across selected periods, allowing users to assess performance trends and absolute quantities over time. Meanwhile, the lower graph offers insights into the indicator's variation, comparing it either monthly or yearly. This comparative analysis aids in identifying seasonal trends, detecting anomalies, and gauging the effectiveness of operational strategies implemented over different time frames. Such insights empower decision-makers to not only react to current trends but also proactively plan for future demands and challenges.

Therefore, the significance of this dashboard lies in its ability to facilitate temporal analysis, enabling stakeholders to track the evolution of scheduling activities and service utilization. By visualizing trends and fluctuations in key metrics, such as scheduling volumes and service ratios, decision-makers can make informed adjustments to resource allocation, optimize operational efficiencies, and pre-emptively address potential bottlenecks or underutilization periods. This proactive approach not only enhances operational performance but also contributes to the overall resilience and competitiveness of port logistics and management strategies.

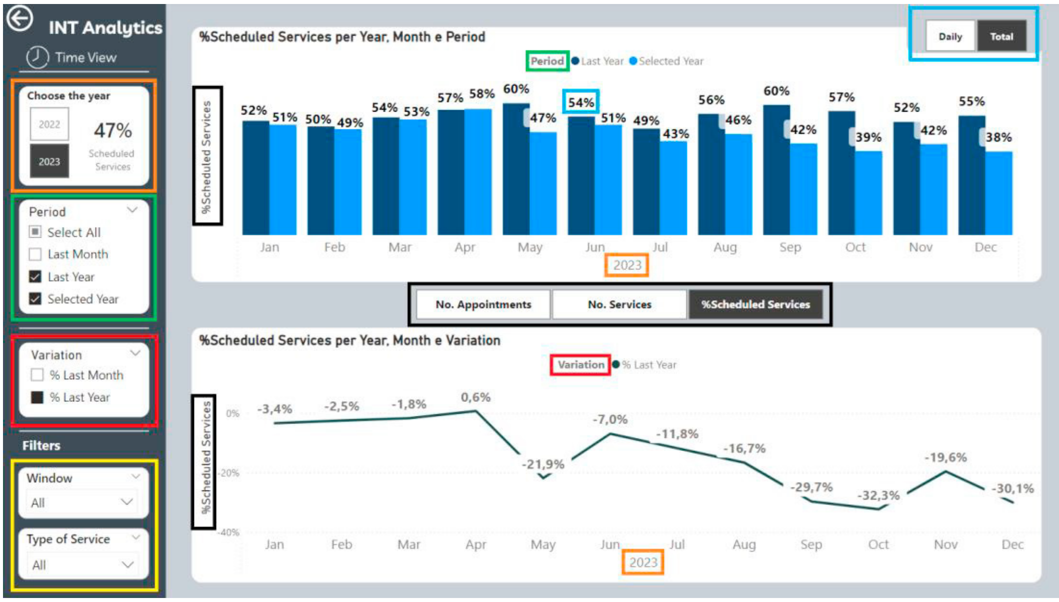

Fig. 4. Time View Dashboard – INT Analytics

The "Compliance" dashboard (Figure 5) is composed of four graphs, each offering distinct analytical perspectives. Users can select indicators and categories for detailed analysis. The top left graph presents values of the selected indicator across different elements of the chosen category. Meanwhile, the bottom left graph displays the '%Compliance of these category elements. On the top right, users can explore how category values correlate with the number of scheduled services. Finally, the bottom right graph visualizes the distribution of services based on compliance with designated time windows, featuring interactive filtering options that synchronize with selections made in other graphs.

Thus, this specific dashboard exemplifies the successful integration of data from different systems, enabling innovative analysis of terminal operations. Although the process of cross-referencing data was complex, it proved to be fundamental for measuring previously inaccessible indicators, such as %Compliance. In this way, integration can increase access to information, improving the depth of analyses and highlighting its crucial role in improving operational performance and guiding strategic decisions more efficiently.

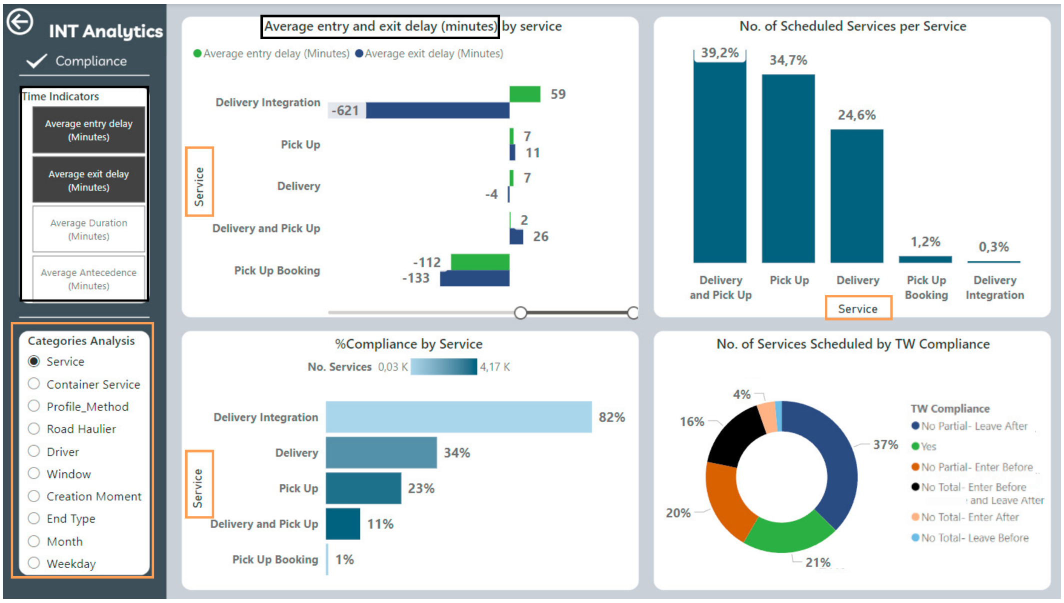

Fig. 5. Compliance Dashboard – INT Analytics

The integration of the KPIs into the dashboards has provided an in-depth understanding of the logistics operations at the port terminal examined. Regarding their focus on scheduling management, service efficiency and compliance with timetables, these dashboards offer valuable information to stakeholders. They not only optimize current resource allocation and operational efficiency, but also improve the terminal's preparedness for future challenges, reinforcing its adaptability in the fast-changing maritime sector.

5. Evaluation: A SWOT Analysis Overview

The BI tool was appraised by the main stakeholders in terms of its potential impact and ability to measure and analyse parameters that until then had not been quantified. Based on the feedback obtained in validation meetings and reflections on the solution in port terminals, an analysis was drawn up reflecting the main pros and cons in terms of their strengths, weaknesses, opportunities and threats (SWOT). Table 3 shows the SWOT analysis that resulted from this study.

Table 3. SWOT analysis of the developed BI System.

	Positive factors	Negative factors
	Strengths	**Weaknesses**
Internal factors	• It measures previously unobtainable indicators (% Scheduled Services, % Compliance) by integrating data from different sources and granularities into a single dashboard. • An appealing graphic presentation that makes it easy to interpret the data immediately. • The tool has various functionalities (time analysis, categories, summary) and allows comparisons to be made between various categories in the graphs; • The structure and data model allow the creation of other dashboards to suit new requirements; • It takes little effort and time to perform future analyses, since the process is structured.	• Using the interface requires some training and understanding on the part of the user, especially the dashboards which allow the dynamic analysis of various categories; • Need specific knowledge to configure the tool and deal with unforeseen events; • Although the cross-referencing mechanism has achieved a representative and crucial sample under the circumstances, this remains limited, and it is necessary to obtain a total correspondence between appointments and services, which requires the development of the integration of the systems involved.

	Opportunities	Threats
External factors	• Develop the integration between the scheduling system and the operating system, capitalizing on the advantages identified by the solution built; • Make the decision-making process more data-driven by using the tool; • Expansion of the use of this type of solution to other terminals in the port under study.	• Data quality, which can compromise the credibility of the tool's analysis; • Resistance to user adoption due to lack of knowledge of the tool's benefits; • The existence of software that is more intuitive to use or allows for more sophisticated analysis.

The BI solution has transformed the landscape of data analysis by providing rapid access to vital KPIs that were historically challenging to obtain. This advancement has not only enhanced the accuracy and depth of analyses but has also enabled stakeholders to make more informed and strategic decisions. A significant advantage lies in the automation and organization of data extraction and visualization processes, which has considerably reduced the time and effort previously required for manual data processing. However, alongside these advancements, there are challenges. For instance, it is crucial to ensure that users receive adequate training to fully leverage all the capabilities of the BI interface. Additionally, upholding high standards of data quality through specialized automated processing is crucial for maintaining the credibility and reliability of analytical results. Despite these challenges, the adoption of BI has positioned organizations to capitalize on opportunities for enhanced systems integration and operational efficiencies. This transformative change not only streamlines current operations but also establishes a foundation for future innovations and strategic developments in data-driven decision-making processes.

6. Conclusions

Data is a crucial asset in any business activity, and the way it is collected and processed is a critical success factor. In a context of constant evolution and change, obtaining quality information in an agile way is essential to ensure business continuity and development. BI tools have established themselves as the main means of achieving this, as they aggregate and structure the entire process of collecting, processing and sharing information, making it accessible and personalized for different users.

In this study, the problem behind the proposed solution was the data dispersion among the different modules of the information systems and the subsequent difficulty involved in processing this data to support certain decisions relating to logistics services at a port terminal. This situation undermined the prior planning of operations, and the resources involved, resulting in significant congestion in a port terminal. Although there is a vast literature on BI, the specific tools for the port sector are still unexplored. The primary objective of this research was to develop a tailored BI tool aimed at enhancing logistics flow analysis, exemplified through its application in a real-world scenario at a Portuguese seaport. This tool effectively demonstrates how BI-driven digitalization accelerates structured analysis, addresses information gaps, and enables informed, data-driven decision-making.

However, the project encountered challenges in data collection and processing due to inconsistencies. The tool's design was influenced by the absence of clear stakeholder guidance, which may limit its relevance to the specific needs of the port. The dashboard's broad range of categories might impact usability and user adoption, especially for those not trained in using the tool.

Despite these limitations, it is recommended to expand this type of solution to other contexts of port terminals based on the methodology adopted, due to the proven ability to make port logistics operations more resilient and effective. Moreover, future research should continue to delve into both the theoretical foundations and practical applications of BI in the maritime sector because investigating additional case studies across different port terminals and logistics sectors will provide valuable insights into the scalability and generalizability of BI solutions in optimizing port operations.

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